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Improving Infrastructure and Accessibility Indicators for Urban Cycling Networks: Measuring the Accessibility Gap for Safer Cycle Routes in London using Detailed Infrastructure Data and Level of Traffic Stress

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Abstract

Planners and urban researchers need to be able to track progress towards achieving high-quality, safe and inclusive cycle networks. Infrastructure and accessibility measures are suitable for this role, though comprehensive cycling indicators are less developed than equivalent public transport measures, due to the challenges in modelling detailed cycling infrastructure and in considering the needs different types of cyclists, including more vulnerable users. In this paper we develop new cycle infrastructure and accessibility measures, firstly developing a classification of cycle lane types based on OpenStreetMap (OSM) data, and secondly classifying wider road conditions using the Level of Travel Stress (LTS) framework. The main innovations here are firstly improving on the standard LTS derivation using commonly available OMS tags and improved junction interpolation; and secondly developing demand-weighted cycle indicators using centrality analysis. Our results show substantial gaps in London's cycle network, with inconsistent cycle accessibility outcomes, particularly in Outer London. The cycle infrastructure data is then used to produce a routable cycle network, and this network is analysed to measure differences in cycling accessibility to core services between experienced and more vulnerable cyclists, based on vulnerable cyclists prioritising safer cycle infrastructure. We observe a substantial accessibility gap for more vulnerable cyclists in London due to the lack of provision of physically separated cycle infrastructure in many boroughs. Finally, the new accessibility measures are validated against travel survey data to assess how closely they correlate with observed cycling behaviour.

KEYWORDS: Cycling accessibility, Level of Traffic Stress, Cycle infrastructure, Network analysis, 15 Minute City, OpenStreetMap

1 Introduction

Increasing levels of cycling is a key part of the transport strategies of many global cities with the potential for significant health and sustainability benefits resulting from greater levels of active travel (Transport for London 2023; EU Commission 2024). Fragmented and poor-quality cycle infrastructure is however a major barrier to widening cycling participation in many countries (Hull and O'holleran 2014; Pucher and Buehler 2016; Hong, McArthur, and Livingston 2020; Shahriari, Siripanich, and Rashidi 2024), including the UK. London is currently expanding its cycling network, which has lagged behind established European cycling cities such as Amsterdam and Copenhagen, and has not matched cities with major network expansions such as Paris. Planners and urban researchers should be able to analyse and track the progress of cities and local authorities towards achieving high-quality, safe and inclusive cycle networks. Infrastructure and accessibility measures are suitable for this role, though comprehensive cycling measures are less developed than public transport and walking accessibility measures, in large part due to the challenges of modelling detailed cycling infrastructure and in considering the needs of different kinds of cyclists.

Two different types of cycle network indicators are developed in this paper: infrastructure measures and accessibility measures. Infrastructure measures summarise the provision and quality of cycle infrastructure. For more vulnerable users, cycle lanes should by physically segregated from motor vehicles, and cycle infrastructure measures need to be able to assess the types of cycle infrastructure provided. Accessibility measures analyse the ease of reaching destinations through cycle and road networks, considering the destinations residents want to reach, providing a measure of how efficiently cycle networks and land use patterns are meeting needs for typical trips. The 15 Minute City concept is used here as a framework for the accessibility analysis, considering accessibility to local services such as retail, education and health. This paper develops infrastructure and accessibility measures that directly consider less experienced cyclists who require physical segregation from motor vehicles and low speed routes. Many accessibility measures assume that cyclists are willing to mix with motor traffic on busier roads, which is not the case for all types of cyclists.

The core dataset used is OpenStreetMap (OSM), which provides detailed information on cycle and street networks and is available globally. To model cycle networks for more vulnerable users, we need a classification scheme of cycle infrastructure, and a comprehensive dataset of cycle infrastructure types is derived from OSM based on Furth (2012). We then use OSM data to improve on the Level of Traffic Stress (LTS) framework, which accounts for wider road conditions that affect cyclists, such as road type, road speed and number of carriageways. We argue in this paper that network analysis is needed for accurate cycle infrastructure and accessibility indicators. For infrastructure measures, it is necessary to understand the extent to which cycle networks match demand and serve the busiest cycle routes. For example, in some London boroughs there is good cycle network provision in more peripheral parks, yet the most in-demand streets linking to retail and public services can have relatively poor cycle infrastructure. Betweenness centrality analysis is used to identify the most frequently desired routes based on network configuration and the location of typical trip destinations. This network measure is then combined with the infrastructure classifications to produce network-weighted cycle infrastructure indicators that more accurately summarise network provision against potential demand.

For accessibility analysis, we also need to route cycle journeys accurately through the network, considering user preferences for cycle infrastructure, particularly for more vulnerable users. One of the most popular open access tools for accessibility analysis, R5, enables cycle routing based on setting an upper limit of cycle infrastructure that cyclists will accept, using a Level of Traffic Stress setting. While this is a useful approach, it is a somewhat blunt tool that has difficulties producing routes for lower LTS settings in mixed cycle infrastructure environments – i.e. the typical context for UK cities. The approach taken here is to use network routing to calculate safer cycling routes, and then compare the accessibility of these safer routes against the more direct cycling routes that allow cycling on busier roads. To create a routable network, we combine the infrastructure and LTS data with survey data on cyclist preferences. This allows the cycle data to be given preference scores at the link level, which can be used for network routing accounting for more vulnerable cyclists. This analysis is based on typical trip types such as shopping, education and health.

A significant challenge for measures of cycle infrastructure and accessibility is how to validate these measures. The approach taken here is to correlate the outputs with measures of cycling mode choice from travel survey data, and link-based cycle counts from Transport for London. This provides a useful guide for how well the measures match observed travel behaviour.

2 Literature Review

We firstly review the importance of cycle infrastructure for increasing cycling levels and expanding participation in Section 2.1. This is followed by a review of cycle infrastructure data sources in Section 2.2, classifications of cycling infrastructure in Section 2.3, and then a discussion of measures of cycling accessibility in Section 2.4.

2.1 Cycle Infrastructure, Uptake and Participation

High-quality, safe cycle infrastructure is widely recognised as a crucial factor in promoting cycling participation (Nelson and Allen 1997; Dill and Carr 2003). Cycle infrastructure can take various forms, including physically separated cycle lanes, on-road lanes without physical barriers, roads shared with motor vehicles without dedicated infrastructure, and off-road paths in natural settings (Furth 2012). Differences in the type and design of cycle infrastructure can significantly affect safety – both actual and perceived – and cycling uptake.

Empirical studies have shown that improvements to cycle infrastructure can increase local cycle participation (Hull and O'holleran 2014; Pucher and Buehler 2016; Hong, McArthur, and Livingston 2020; Shahriari, Siripanich, and Rashidi 2024), enhance confidence and sense of legitimacy especially for inexperienced cyclists (Clayton and Musselwhite 2013), and increase cyclists' safety by reducing accidents (Mulvaney et al. 2015). Importantly, research suggests that the type and quality of infrastructure shapes user preferences, which in turn influences overall cycling uptake. Using GPS trajectories of cyclists in Denmark, Łukawska et al. (2023) found that cyclists prefer protected cycle lanes to minimise interaction with vehicles and favour routes through natural settings. Similarly, Steer Davies Gleave (2012) quantified the relative importance of London's cycle infrastructure types using survey data, with cyclists substantially preferring greater separation and protection from motor traffic. These preferences are important as they translate into participation outcomes. Studies show that physically separated cycle tracks are more influential in encouraging cycling compared to lower quality infrastructure provision (Pucher and Buehler 2016). Moreover, the development of fully segregated cycle lanes, together with a well-designed cycling network, has been shown to significantly increase cycling in cities with no prior cycling tradition, as demonstrated in Seville (Marqués et al. 2015).

2.2 Cycle Infrastructure Data Sources

Given the importance of cycle infrastructure for improving cycling safety and participation, analysing and tracking its provision is crucial. Yet cycle infrastructure data is often limited, with consistent and comprehensive cycle infrastructure databases lacking in many countries, including the UK. London's Cycling Infrastructure Database (CID) offers detailed data on cycle infrastructure types in Greater London (Transport for London 2019). This dataset only however represents a snapshot from 2017-2018, and has not yet been updated to capture more recent cycle infrastructure improvements. The need to analyse cycle infrastructure at scale has therefore turned researchers toward open crowd-sourced datasets, most notably OpenStreetMap (OSM).

The most straightforward way of identifying cycle infrastructure in OSM is using the highway key. Gehrke et al. (2020) identified cycle infrastructure in OSM using road class, assigning speed values and priority indices that captured differing preferences and calculated aversion factor for different types of cyclists. Mahfouz, Lovelace, and Arcaute (2023) developed weighted profiles based on OSM road types to reflect cyclist preferences for each type of infrastructure in routing. Williams et al. (2024) defined cycle infrastructure using typical OSM tags, such as cycleway, path, track, or footway. Wasserman et al. (2019) and Ferster et al. (2020) categorised cycle infrastructure into four types using highway and cycleway tags in OSM, applying these classifications to Level of Traffic Stress calculation and cycle infrastructure inventories in Canadian cities, respectively. OSM data can however include gaps and inconsistencies due to its crowd-sourced nature. To address this, researchers have employed different imputation strategies. Wasserman et al. (2019) inferred missing attributes such as lanes and speed limits from OSM's functional classification, making assumptions about roadway characteristics to enable Level of Traffic Stress calculations. Harvey, Rodríguez, and Fang (2024) adopted a more conservative approach, assuming the absence of infrastructure (e.g., no bike lane) where data were missing and only estimating values when clear relationships could be established, thereby reducing the risk of overstating cycle infrastructure quality.

2.3 Cycle Infrastructure Classifications - Level of Traffic Stress

Level of Traffic Stress (LTS) is a widely used metric for assessing the cycling safety of roads by considering road attributes (Mekuria, Furth, and Nixon 2012; Furth, Mekuria, and Nixon 2016). LTS assigns stress levels to road segments using a four-tier scale, where LTS level 1 indicates safe and comfortable cycling conditions for all cyclists, including vulnerable users, and LTS level 4 indicates cyclists are required to mix with busy road traffic, producing high stress and potentially dangerous conditions only suitable for experienced cyclists. The original method developed by Mekuria, Furth, and Nixon (2012) requires many detailed variables on infrastructure and road conditions, which can be difficult to obtain for many cities. As a result, more simplified and context-specific versions of the LTS method have been developed.

Conveyal (2015) developed a streamlined LTS classification using a reduced number of common attributes found in OpenStreetMap (OSM) data. Lowry, Furth, and Hadden-Loh (2016) further advanced the LTS framework by incorporating the economics concept of marginal rates of substitution, defined as the additional distance cyclists are willing to travel to avoid higher-stress (e.g. LTS 3 and 4) conditions, and applied it to their case study city of Seattle using readily available data. Moran et al. (2018) modified the LTS scheme to address the absence of detailed traffic signal and functional priority data. Tucker and Manaugh (2018) further simplified the LTS classification method in two Brazilian cities by relying on just a single attribute (highway type) obtained from OSM labels and assigned weights to each LTS level. Montgomery County (2018) expanded the

LTS scale by adding new levels—LTS 0, LTS 2.5, and LTS 5.0— to provide a granular assessment and bridge the large gaps between existing LTS levels. However, the Montgomery method requires input variables that are typically not accessible in publicly available datasets, such as raised median and driveway counts (Harvey, Rodríguez, and Fang 2024). Huertas et al. (2020) developed a data-informed LTS-based classification methodology by conducting a cluster analysis on a representative sample of the road network and training a machine learning classifier (multinomial logistic regression) to categorise all segments of the city-wide road network into clusters. Each cluster was assigned an LTS category based on specific attributes, effectively avoiding difficult classification decisions.

While LTS provides an intuitive way of analysing cycling safety, it has some limitations. Firstly, most existing LTS schemes are tailored to Northern American urban contexts (Mekuria, Furth, and Nixon 2012; Lowry, Furth, and Hadden-Loh 2016; Imani, Miller, and Saxe 2019) and require relatively detailed, localised datasets for these urban settings (Mekuria, Furth, and Nixon 2012; Montgomery County 2018). Furthermore, many APIs or software that automate LTS assignment often operate as black-box tools, limiting its applicability for transparent international studies. Lastly, existing LTS schemes can over-simplify detailed cycle infrastructure. While some account for bike-specific facilities, they typically require extensive data inputs, such as lane width and bike lane blockages (Furth, Mekuria, and Nixon 2016; Montgomery County 2018) or rely on pre-compiled datasets by local governments (Lowry, Furth, and Hadden-Loh 2016). These requirements can pose challenges, particularly where such detailed information is unavailable or inconsistent. Additionally, LTS-based routing software typically applies a maximum LTS cut-off to calculate accessibility (Lowry, Furth, and Hadden-Loh 2016; Pereira et al. 2021). While useful for broad comparisons, this approach is relatively simplistic, as it overlooks more nuanced factors such as perceived safety or varying cyclists' infrastructure preferences. Taken together, these instances underscore the need not only to adapt LTS schemes to the UK as well as other similar European contexts, but also to refine the methods to incorporate more flexible, transparent, and nuanced representations of cycling conditions.

2.4 Cycling Accessibility Analysis

Most existing cycling accessibility studies are typically based on travel time or distance. For instance, Iacono, Krizek, and El-Geneidy (2010) modelled accessibility by incorporating distance-based decay to reflect how destinations become less attractive as distance increases. Lowry, Callister, et al. (2012) calculate bikeability as an accessibility measure, where the impedance of traveling to destinations is modelled using distance weighted by bike level of service scores. McNeil (2011) evaluated cycling accessibility in Portland by developing a bikeability score based on the range of daily destinations reachable within a 20-minute ride. Saghapour, Moridpour, and Thompson (2017) developed a gravity-based Cycling Accessibility Index for Melbourne that incorporates land-use diversity, the number of opportunities, and travel distance to quantify cycling accessibility.

Accessibility measures primarily based on time and distance can be misleading for vulnerable cycle users where cycle safety and comfort are not taken into account. Some researchers have pursued a more comprehensive approach, incorporating factors such as safety and comfort in addition to time and distance. Winters et al. (2013) developed a bikeability index incorporating cycle infrastructure availability and quality, street connectivity, topography, and land use, all of which influence cycling. Lowry, Furth, and Hadden-Loh (2016) evaluated residents' access to utilitarian destinations using low-stress cycle routes. Imani, Miller, and Saxe (2019) assessed cycling accessibility in Toronto using the LTS framework, showing that while many local streets are low stress, high-stress arterials fragment the network into "islands" that restrict access to jobs and destinations without crossing stressful roads. While these studies provide a more comprehensive picture of cycling accessibility, they are limited by reliance on datasets specific to certain urban contexts and by challenges in quantifying accessibility for comparisons between cities and neighbourhoods.

3 Methodology

This section describes how the cycle infrastructure classifications are produced from OpenStreetMap (OSM) data. Firstly, in Section 3.1.1, we discuss how OSM is a suitable dataset for describing detailed cycle networks. OSM is also the source of the trip destinations – Points of Interest – used in the network analysis. In Section 3.2 and 3.3 we show how to derive the cycle infrastructure classification and Level of Traffic Stress classification using the OSM data. The first classification (3.2) is a direct measure of types of cycle lanes derived from OSM. The second Level of Traffic

Stress framework (3.3) is a wider classification of the suitability of every road link for cycling based on factors such as road classification, speed and number of carriageways. Some adjustments from the standard LTS model are developed to improve the LTS classification for the UK context. In Section 3.4, we convert the infrastructure types identified in Section 3.2 into preference scores. Then in Section 3.5 the cycle infrastructure classification and LTS data are combined to enable routing analysis of the full urban network incorporating the cycle infrastructure preferences of different users. The final aspects of the methodology relate to network analysis and routing. A betweenness centrality measure is developed in Section 3.6 to estimate cycle link demand for more accurate measures of cycle infrastructure quality.

3.1 Data

3.1.1 OpenStreetMap Data for Cycle Infrastructure and Network Routing

OpenStreetMap (OSM) is a crowd-sourced geospatial data platform where users contribute and access detailed information on the built environment. OSM is frequently updated, integrates public datasets (including TfL's Cycle Infrastructure Database), and offers extensive coverage, making it a valuable source of both high-quality and high-volume-spatial data. OSM provides link-level detail on a variety of road types suitable for active travel modes (Schlosser et al. 2025) as well as diverse forms of cycle infrastructures (Wasserman et al. 2019; Lovelace and Talbot 2025). This granularity allows OSM to be used in constructing cycle networks. The data has also demonstrated its scalability in large network analyses (Louf and Barthelemy 2014; Lovelace, Goodman, et al. 2017) and transferability across different countries (Manley, Filomena, and Mavros 2021; Boeing 2022). In this regard, OSM offers both the detail and adaptability needed for assessing cycle infrastructure across different urban contexts.

The cycle network data forms the foundation for constructing the cycling network and identifying detailed cycle infrastructure information. Using the Python package "Pyrosm" (Tenkanen 2020), the cycle road network within Greater London was extracted. Each road segment contains detailed attributes such as road classification, cycle infrastructure type, number of lanes, and speed limit. Notably, OSM often represents roads as several small segments, rather than a single continuous link. Each of these segments carries its own attributes, which is particularly valuable when cycle infrastructure is only present along part of a road. This level of granularity allows for a more accurate street-level evaluation of cycling conditions.

POIs serve as destination points in the routing analysis. The POI data extraction query focuses on three keys: amenity, shop, and tourism. These categories relate to the core urban services highlighted in the 15 Minute City: living, working, healthcare, commerce, education, and entertainment (Moreno et al. 2021). In this way, these POIs include the most common trip destinations and reflect the services most likely to influence cycling behaviour and accessibility patterns. Initially, the dataset contained over 250,000 POIs, and after filtering out irrelevant and permanently closed POIs and retaining only those relevant to the 15 Minute City, around 67,000 POIs remained.

3.1.2 Census Geography

It is useful to be able to link the cycling accessibility analysis to demographic data from the census, such as population levels and journey to work data on cycling commuting levels. Lower Super Output Area (LSOA) centroids are used as origin points for routing analysis. LSOAs are the second-lowest level of census geography in the UK, each covering between 400 and 1,200 households (typically 1,000 - 3,000 residents) (ONS 2011). There are 4,969 LSOAs in Greater London, providing a granular set of origin points for analysis while remaining computationally manageable.

3.1.3 Cycle Flow Validation

To validate the cycle network measures produced, we correlate the results with cycle demand data at two different scales: link level and area level. For link-level validation, Transport for London (2024) provides link-level cycle count data at 1451 monitoring stations which are representative of the cycle network in London. The counts took place at each site over 16 hours (6:00 – 22:00) on weekdays (between Tuesday and Thursday) in spring (between April and July) in 2024. Each panel of locations is stratified by the area (Central, Inner and Outer London) and the road type (A road, B road, minor road, local streets and motor vehicle-free paths) to provide a representative sample of road types.

For area-based validation, several survey datasets were used. The 2011 journey to work data was obtained at the Middle layer Super Output Area (MSOA) level. The data contains residence, workplace, total commuting populations, and cycling populations, enabling the calculation of cycling mode share by MSOA. The 2021 journey to work data for trips under 10km was available at the Local Authority District (LAD) level. Additionally, the Active Lives Survey data (Department for Transport 2024b) was derived at the LAD level which contains cycling rates for all trip purposes. However, data were available for only 31 of the 33 London local authorities, resulting in partial borough-level coverage.

3.2 Deriving Cycle Infrastructure Classifications from the OpenStreetMap Data

Before categorising cycle infrastructure, the road network dataset was pre-processed to exclude highway types that are either mis-specified, misspelled in OSM or unsuitable for cycling (e.g. *cycleway way* – misspelling of cycleway -, *motorways*, *busways*, or segments under construction). This filtering step not only ensures that only potentially cyclable links remain in the network but also avoids reliance on highway types that may be specific to individual urban contexts. In this way, the set of retained highway types remains coherent and comparable across different urban settings.

The cycle infrastructure classification used in this study is based on the four categories proposed by Furth (2012) with minor adjustments to better reflect UK and similar European urban contexts. We extend this definition by introducing a fifth category: unprotected advisory cycle lanes. Unlike either physically segregated lanes or unprotected mandatory cycle lanes, which are reserved solely for cyclists and separated from motor traffic by paint or markings, unprotected advisory cycle lanes are shared with motor vehicles but are visually indicated by markings that provide cyclists with greater visibility and a degree of prioritisation. A common example in the UK is a bus lane that legally permits cycling, where riders benefit from wider lanes and lane markings despite sharing the lane with buses. To operationalise this classification, the literature-based definitions were translated into the OSM tagging system, which defines infrastructure elements in its own terms. By aligning the conceptual typology with OSM tags, we derive street-level cycle infrastructure from OSM data.

To infer detailed cycle infrastructure from OSM, we primarily use the '*cycleway*', '*highway*', and '*bicycle*' keys, alongside additional contextual '*tags*'. The '*cycleway*' key provides the most direct information on the presence and type of cycling facilities (Wasserman et al. 2019; Lovelace and Talbot 2025), though it is often incomplete or inconsistently applied. The '*highway*' key classifies road types and functions, offering insights into the level of basic cycling provision (Gehrke et al. 2020; Mahfouz, Lovelace, and Arcaute 2023; Williams et al. 2024). The '*bicycle*' key encodes permissions and rules for cyclists on particular links. While it does not directly describe infrastructure, certain values provide useful indications of access conditions, such as whether cycling is officially designated or whether riders are required to use an adjacent side path, equivalent to separated cycleways. The '*tags*' supplies additional contextual details on the characteristics or intended use of a road segment. It consists of a key-value pair that describes specific attributes of a road element, such as separation from traffic, or conditional usage. In this way, the '*tag*' captures nuanced aspects of cycle infrastructure and helps fill gaps left by the more general keys, including '*highway*', '*cycleway*', or '*bicycle*'.

Using these OSM tags, we inferred street-level cycle infrastructure. Protected cycle lanes include cycle tracks, stand-alone cycleways explicitly designed for cycling, and separately mapped cycle paths. Unprotected mandatory cycle lanes are on-road facilities reserved for cyclists without a physical barrier, whereas unprotected advisory cycle lanes are marked cycling spaces shared with motor vehicles. Off-road links capture cycle routes in natural or recreational settings. Road segments that do not fall into any of these categories are classified as roads without dedicated cycle infrastructure (See Table 1).

Category	Definition	OSM mapping approach	Notes
Protected Cycle Lane (a) Cycle tracks	Cycle tracks running adjacent to roads, but mapped as attributes of the carriageway	`cycleway=track`; `cycleway:right=track`, `cycleway:left=track`	Represents physically separated tracks linked to road segments
Protected Cycle Lane (b) Designated cycleways	Cycleways mapped as separate geometries, explicitly reserved for cyclists	`highway=cycleway` (excluding shared busways/lanes via filtering of tags)	Independent geometries in OSM, representing dedicated cycle paths
Protected Cycle Lane (c) Separated cycleways	Cycle paths mapped separately from roads, with cyclists required/encouraged to use them	`cycleway=separate`; `cycleway=sidepath`; `bicycle=use_sidepath`	Indicates that a parallel, separately mapped cycle path exists
Unprotected Mandatory Cycle Lane	On-road lanes reserved solely for cyclists, separated only by paint/markings	`cycleway=lane`; lane-related tags (excluding shared busways/lanes)	Marked lanes without physical separation; higher priority than advisory lanes
Unprotected Advisory Cycle Lane	On-road lanes marked for cycling but not exclusively reserved; motor vehicles may enter or stop	`cycleway=advisory`; `cycleway=shared`; `cycleway=share_busway`; `cycleway=shared_lane`	Marked lanes without physical separation; lower priority and weaker protection than mandatory lanes
Off-Road	Paths away from carriageways, often in natural settings	`highway=path`; `highway=track`; `highway=footway + bicycle=designated or bicycle=yes`	Captures natural or recreational settings, including shared-use paths with pedestrians or trails

Note. A road segment not belonging to any of the above categories is classified as a road without cycle infrastructure.

Table 1: Mapping detailed cycle infrastructure from OSM

3.3 Improving the Level of Traffic Stress Model

Our research introduces an improved Level of Traffic Stress (LTS) scheme, building on the Conveyal LTS model (Conveyal 2015). The Conveyal scheme requires a minimal set of variables commonly found in OSM data attributes (ibid.) and has been increasingly used in cycling accessibility analyses (Pereira et al. 2021; Lovelace, Félix, and Carlino 2022; Williams et al. 2024). Furthermore, the model appears to be conceptually robust, delivering consistent results regardless of different datasets being used (Harvey, Rodríguez, and Fang 2024). The Conveyal LTS model follows a two-step process. In the first step, initial LTS values are assigned to road segments based on straightforward conditions in relation to road classification, number of lanes, speed limits, and cycleway tags. These conditions are not comprehensive enough to cover all road segments, and so some roads are left without an assigned LTS, with the expectation that they will be resolved in the following step. In the second step, an unsignalised intersection adjustment is applied. At each junction, the highest LTS value from any connecting road is extended to all intersecting roads. This process both fills some of the gaps left from the previous step and also reflects the higher stress levels that cyclists may encounter in mixed-traffic environments.

The Conveyal model does however have some limitations. Firstly, its performance relies on the completeness of the crowd-sourced datasets and the scale of the network being analysed. When key attributes such as speed limits, lane counts, or cycleway tags are missing, especially in large-scale urban networks with millions of edges, the intersection adjustment step is often unable to fill in the gaps in LTS values that occurred during the initial step. Secondly, the LTS assignment criteria for the number of lanes and maximum speed are not tailored to the UK context (or indeed similar European countries), as the UK's historic urban environment often features narrower roads, fewer lanes, and stricter speed limits (UK Government 2024; Department for Transport 2024a). Another limitation is that the intersection adjustment logic used in the Conveyal model does not account for traffic signals or stop signs at intersections. This can potentially overlook the impact of traffic controls that significantly influence LTS ratings at junctions.

To address these limitations, our augmented LTS scheme assigns initial LTS values to all road segments, including those road types that were not covered in Conveyal's initial step. In doing so, we draw on the cycling weighting profile from the Routino project (Bishop 2008), which provides guidance on the relative importance of different road types for cycling. Each road type is classified into an appropriate LTS level, ensuring that every road segment is assigned of an initial LTS value. This approach prevents the gaps in LTS values that the Conveyal model left unsolved in its intersection adjustment step. Furthermore, LTS conditions regarding lane counts and speed limit were adapted to better align with the UK context, incorporating local road features as outlined in the TfL Cycling Action Plan 2 (Transport for London 2023). We introduced a signalised intersection adjustment to account for the presence of traffic signals and stop signs (Imani, Miller, and Saxe 2019; Imrit et al. 2024). At each junction, the baseline LTS is first set to the highest value among the intersecting road segments, reflecting the potential stress of mixed-traffic conditions. This value is then adjusted downwards when traffic controls, such as stop signs and traffic signals, are present as they improve crossing safety. For example, low-stress intersections (LTS 1 - 2) with traffic signals are adjusted to LTS 1, while mixed-stress intersections, where low-stress (LTS 1 - 2) roads meet high-stress (LTS 3 - 4) roads, are adjusted downward (e.g. LTS 4 to LTS 3, or LTS 3 to LTS 2). In this way, the adjustment incorporates both the maximum stress from connecting roads and the mitigating effect of intersection controls, producing more realistic LTS values at junctions. Based on this improved LTS model, LTS values were then computed for all roads in London as a case study.

3.4 Cycle Infrastructure Classification for Network Routing Using Cycle Preferences

To convert infrastructure types into preference scores for routing and accessibility measures, each cycle infrastructure type was assigned a weight based on the cycle route choice model developed for Transport for London (TfL) (Steer Davies Gleave 2012), stratified for the general population (Table 2). The model distinguishes between five infrastructure categories: off-road, mandatory cycle lanes, advisory cycle lanes, bus lanes, and roads without infrastructure. Mandatory cycle lanes refer to marked lanes with greater width, while advisory cycle lanes correspond to narrower facilities. In our study, the classification also includes protected cycle lanes, which are not explicitly represented in the TfL model. To approximate their effect, we assigned the coefficient for mandatory cycle lanes to protected cycle lanes. While this likely underestimates their true relative attractiveness—since protected cycle lanes are generally preferred over painted ones—it nonetheless allows us to capture their relative importance and ensure comparability across infrastructure types.

Type	Description	Score
Off-Road	Cycleways in natural settings, such as parks or rivers	1.00
Protected Cycle Lane	Physically separated from motor traffics	0.31
Unprotected Mandatory Cycle Lane	Painted cycle lanes without physical barriers	0.21
Unprotected Advisory Cycle Lane	Shared with vehicles, yet markings and lanes are indicated for cyclists	0.18
Road	No dedicated cycle infrastructure	0.00

Table 2: Descriptions of cycle infrastructures and preference score rescaled to a range of 0 and 1

Preference scores capture how cyclists value cycle lanes, but they largely overlook broader traffic conditions that the LTS scheme covers that influence perceived safety. For example, a protected cycle lane on a high-speed arterial road may score highly in terms of infrastructure preference but would still impose significant stress due to speed and traffic volume. By combining preference scores with LTS ratings, we integrate user preferences with the objective stressfulness of the road environment, yielding a more behaviourally realistic representation of cycling conditions.

3.5 Cycle Infrastructure Classification Final Weights

LTS values were normalised to a scale between 0 and 1 to ensure comparability with preference scores. Roads with LTS 1 were assigned the highest weight of 1, followed by LTS 2 (0.75), LTS 3 (0.5), and LTS 4 (0.25), reflecting cyclists' preferences for lower-stress environments (Broach, Dill, and Gliebe 2012; Mekuria, Furth, and Nixon 2012). Although these weights do not fully capture the precise importance of each LTS level on the cyclist behaviour, prior empirical evidence suggests a reasonably linear relationship between LTS levels and cyclists' satisfaction (Harvey, Fang, and Rodríguez 2019). The emphasis here is on capturing relative differences rather than estimating the exact extent to which one is more critical than another.

The final weights were derived by combining the normalised LTS scores (representing road safety/stress) with the infrastructure preference scores, assigning equal importance to both factors. The resulting weights were then applied to approximately 1.4 million road segments across London, as a case study (see Figure 1).

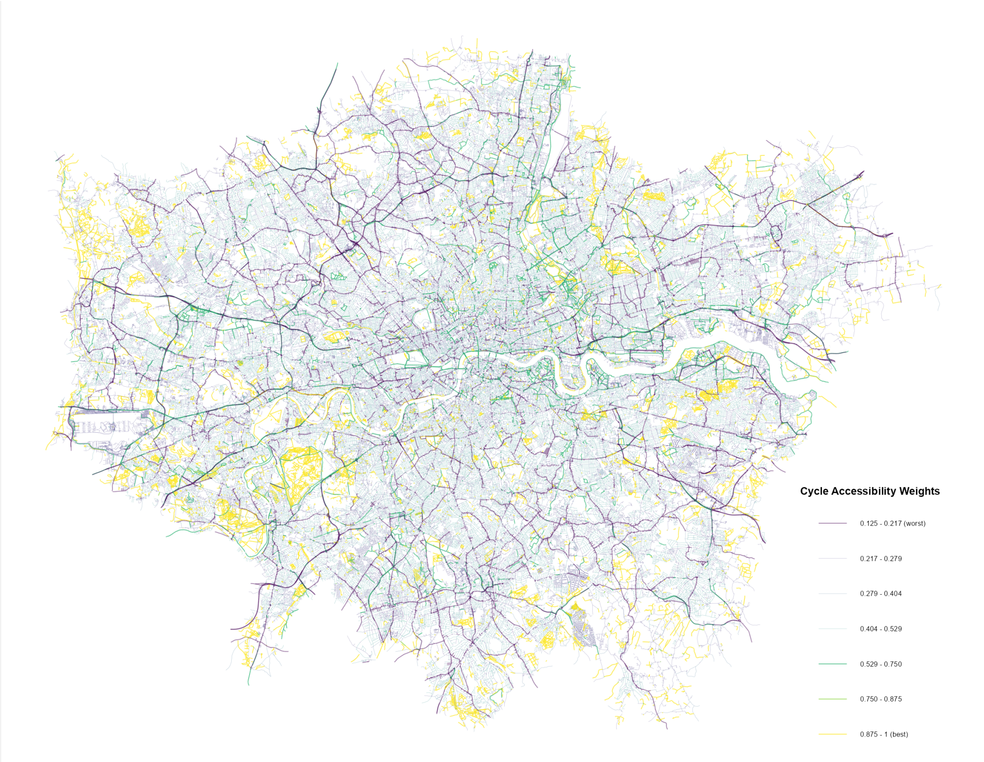


Figure 1: Cycle accessibility final weights for all roads in Greater London

3.6 Centrality Analysis for Estimating Cycle Link Demand

Understanding which routes are most in demand by cyclists is necessary for effective transport planning and infrastructure investment. Centrality analysis provides a systematic way to identify the relative importance of individual road segments within a network, highlighting those links that are likely to experience higher demand. In particular, edge betweenness centrality quantifies how frequently individual road segments are likely to be used by cyclists as part of their journeys between origin and destination points, offering a proxy measure for potential cycling flows.

In this study, origin points were defined as the centroids of Lower Super Output Areas (LSOAs), and destinations were points of interest (POIs) that serve daily needs such as retail, education, and healthcare. To reduce computation, POIs were projected onto granular H3 hexagons at level 10, and centre of mass of POIs within hexagons was then computed as the representative destination point. A maximum isodistance of 15km was set to constrain origin-destination (OD) pairs, representing a realistic upper bound for cycling trips (corresponding to approximately 60 minutes of cycling travel). OD pairs exceeding this threshold were excluded, as they are unlikely long-distance cycling journey. Betweenness centrality was then computed for each unique OD pair, estimating the frequency with which each road in the cycling network lies on the shortest path between all valid OD combinations. In the context of cycling, this metric serves as a proxy for predicting likely cycle flows across the network, and can be used for weighting infrastructure-based cycle accessibility measures.

Figure 2 illustrates edge betweenness centrality across Greater London. High centrality values are observed along main roads that provide access to town centres and Inner London, while peripheral residential roads and more isolated cycleways within parks exhibit lower centrality scores, highlighting their limited contribution to strategic connectivity.

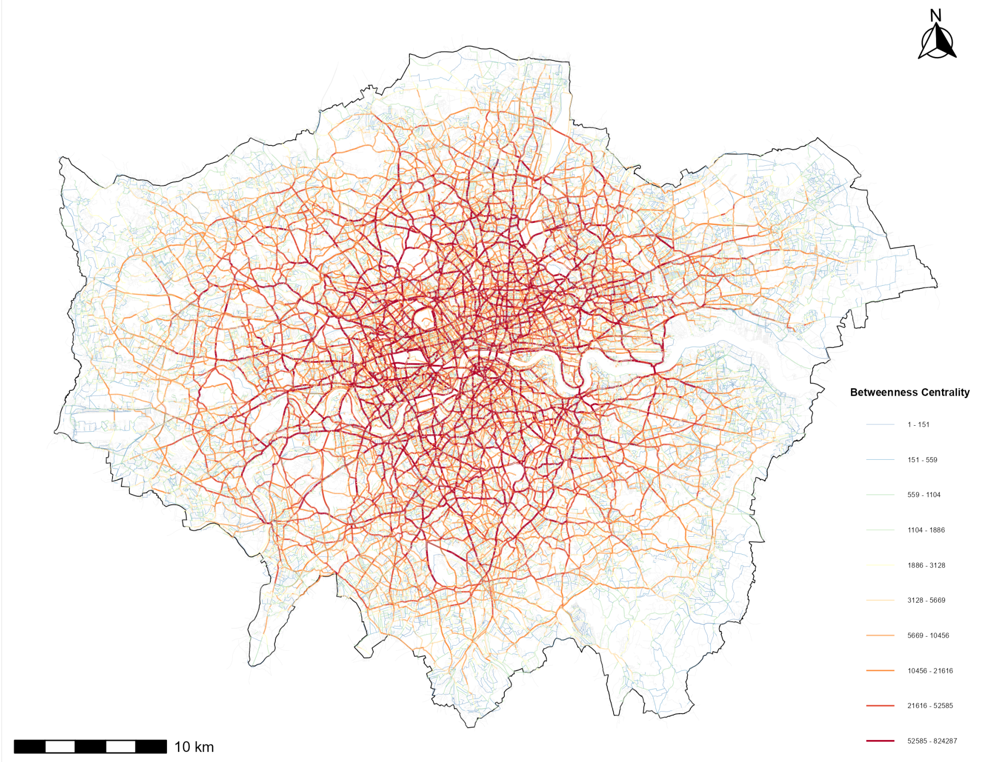


Figure 2: Edge betweenness centrality between LSOA centroids and POIs for common trip types in Greater London with a 60-minute cut off

4 Results

We present the cycle infrastructure indicators in Section 4.1, which summarise the quality and completeness of cycle infrastructure provision in London through mapping and borough-level indicators. The first set of infrastructure indicators in 4.1.1 uses the cycle infrastructure classification, and the second set in 4.1.2 uses the Level of Traffic Stress classification, considering a wider set of factors. These two approaches are then compared and combined into a single network in Section 4.1.3. Next, the accessibility analysis for safer cycle routes is presented in Section 4.2, based on routing trips through the network described earlier in 4.1, and comparing the accessibility between direct routes and safer routes for vulnerable and inexperienced cyclists. Finally, validation of the analysis against travel behaviour data is presented in Section 4.3.

4.1 Cycle Infrastructure Indicators

4.1.1 Cycle Infrastructure Classification for Greater London

The Cycle Infrastructure Classification describes the presence or absence or cycle lanes, and the types of lanes provided, as shown for Greater London in Figure 3. Overall, London's cycle network appears rather fragmented and unevenly distributed, reflecting the varied policies and approaches by local authorities over several decades. Efforts to create a fully integrated city-wide network are more recent, with the Mayor and Transport for London developing city-wide routes through longer distance Cycleways. These are visible in blue on the map, such as the route along Embankment east-west through Central London along the River Thames, and the cycle routes east of the City through Tower Hamlets. The highest quality routes are the protected (i.e. physically segregated) cycle lanes, shown in blue for on-road routes and green for off-road cycle lanes in parks and by rivers/canals. The park-based routes are overwhelmingly in Outer London, particularly north-east around Hackney and Waltham Forest, and south-west in Richmond and Hounslow.

Inner London's complicated cycle infrastructure geography is shown in Figure 4. Inner London has denser cycling infrastructure than Outer London, with more on-road cycling facilities. This on-road provision is quite mixed in quality, including some fully protected segregated lanes on major radial routes (these are TfL Cycleways), some unprotected advisory cycle lanes – these include shared bus lanes and some shared low speed routes in Low Traffic Neighbourhoods such as in Hackney and Islington – and some older unprotected on-road lanes. Overall, cycle infrastructure

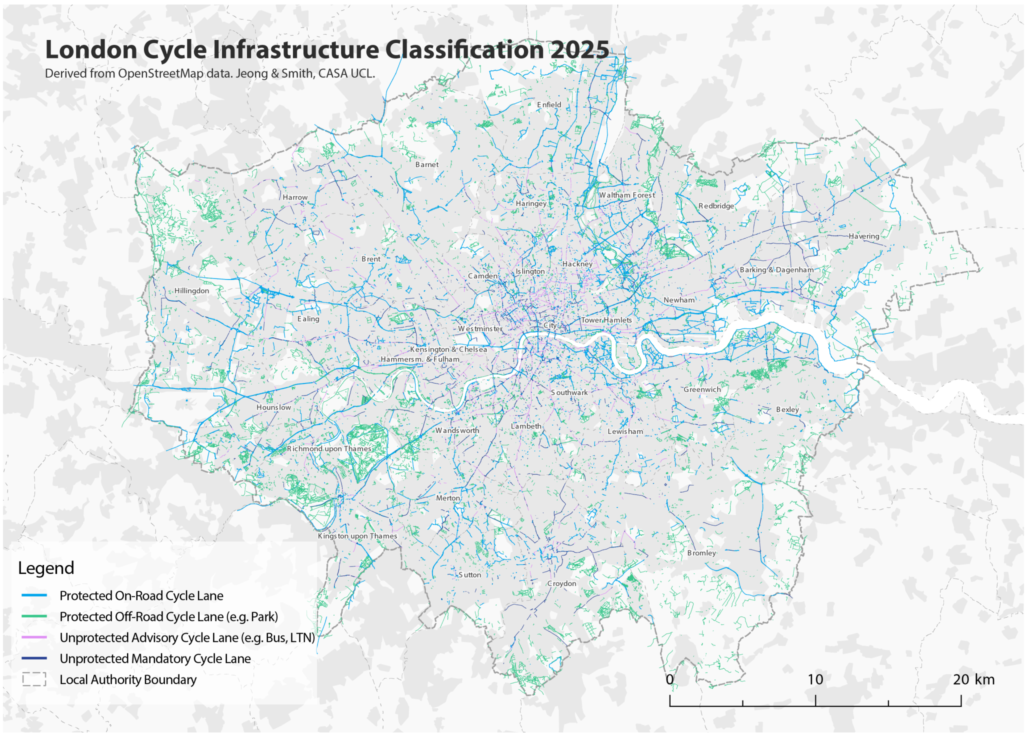


Figure 3: Greater London's cycle infrastructure derived from OpenStreetMap

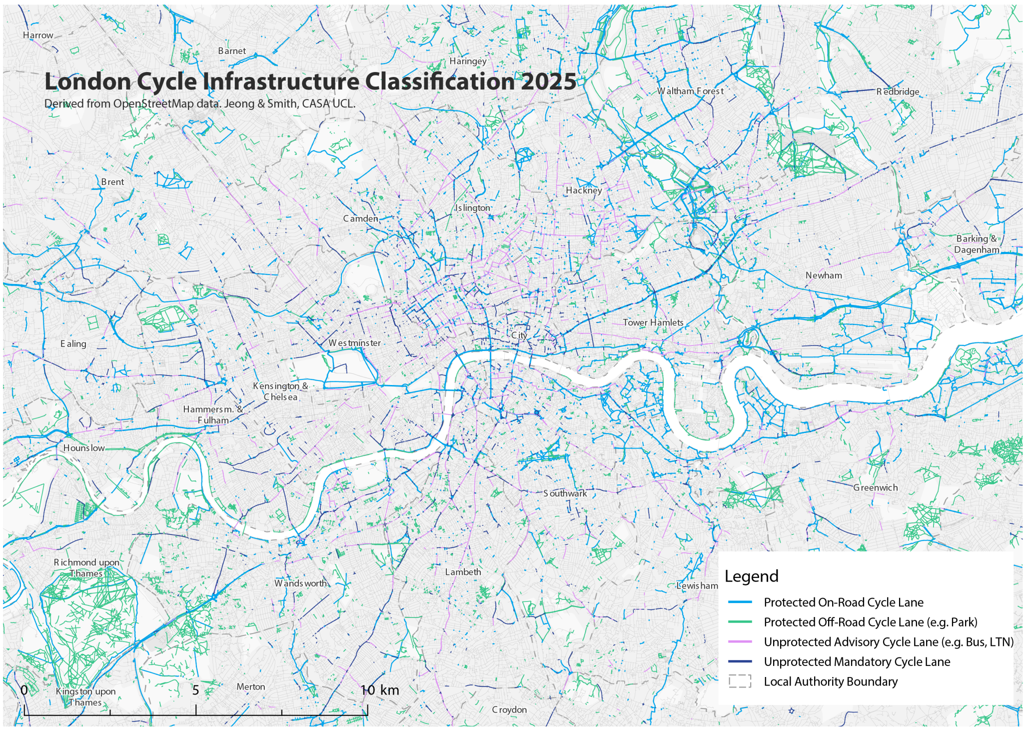


Figure 4: Inner London's cycle infrastructure derived from OpenStreetMap

provision is better in Inner London but is mixed, with a lot of investment still needed to create a fully integrated network.

We can also summarise the cycle infrastructure data at the borough level to provide a simpler overview for local authorities, as shown in Figure 5. This indicator is centrality-weighted, so that roads and streets with high potential cycle demand are weighted more highly compared to low demand roads and streets. To calculate this, each road segment was weighted by its log-transformed betweenness centrality to capture its strategic importance within the wider cycle network. The proportion of each infrastructure type was then calculated relative to the total centrality-weighted cycleway length for each borough. This approach highlights not only the extent of provision but also the relative importance of each infrastructure type in supporting cycling across the network.

The boroughs in Figure 5 are ordered by the provision of high-quality cycle infrastructure (protected cycle lanes and off-road cycle lanes separate from road traffic). The leading boroughs by this measure are in Outer London, led by Waltham Forest, Richmond-upon-Thames and Hounslow. Greenspace provision plays a role in this result, particularly in Richmond, which has the highest contribution of off-road cycle lanes. The contribution of off-road cycle lanes is however relatively modest in Waltham Forest and Hounslow (due to the centrality weighting) and in-fact these boroughs are at the top of the list mainly through their protected cycle lanes. Waltham Forest has been implementing pro-cycling policies for several decades, including the "Mini-Holland" Mayoral funding programme in the 2010s. While these Outer London boroughs score well, the wider Outer London picture is mixed, with several more car-dependent boroughs –such as Barnet, Brent and Harrow – close to the bottom of the list.

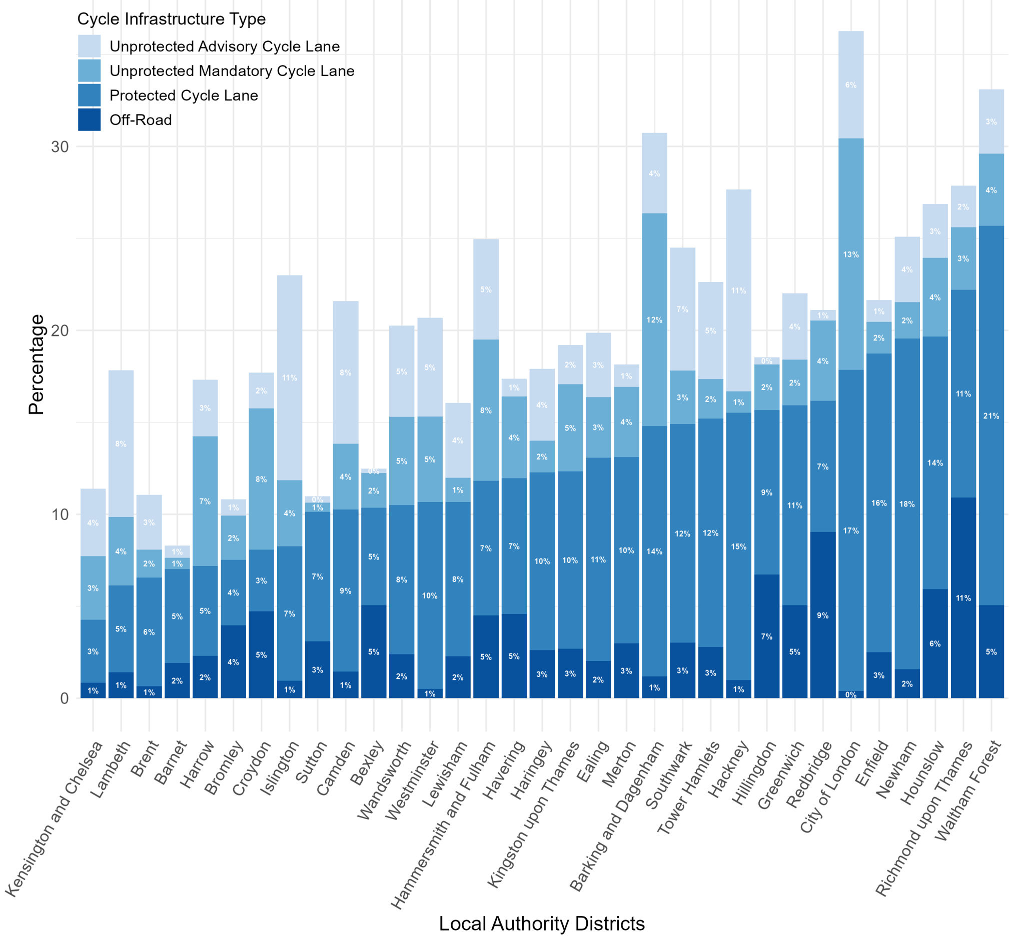


Figure 5: Proportion of centrality-weighted cycle infrastructure across Greater London, ordered by high-quality cycle infrastructure (sum of off-road and protected cycle lane)

The results for Inner London boroughs are also mixed. Several Inner London boroughs have a high proportion of lower quality cycle lanes that are not physically segregated from vehicles, including the City of London, Hackney and Hammersmith. These are generally shared bus lanes, or in the case of Hackney, Low Traffic Neighbourhoods. Several Inner London boroughs score unexpectedly poorly with this measure, including Lambeth, Islington and Camden (again these have substantial proportions of unprotected cycle lanes). Kensington and Chelsea scores last – a very poor result for a wealthy Inner London borough – reflecting historic resistance to cycle lane development in this borough.

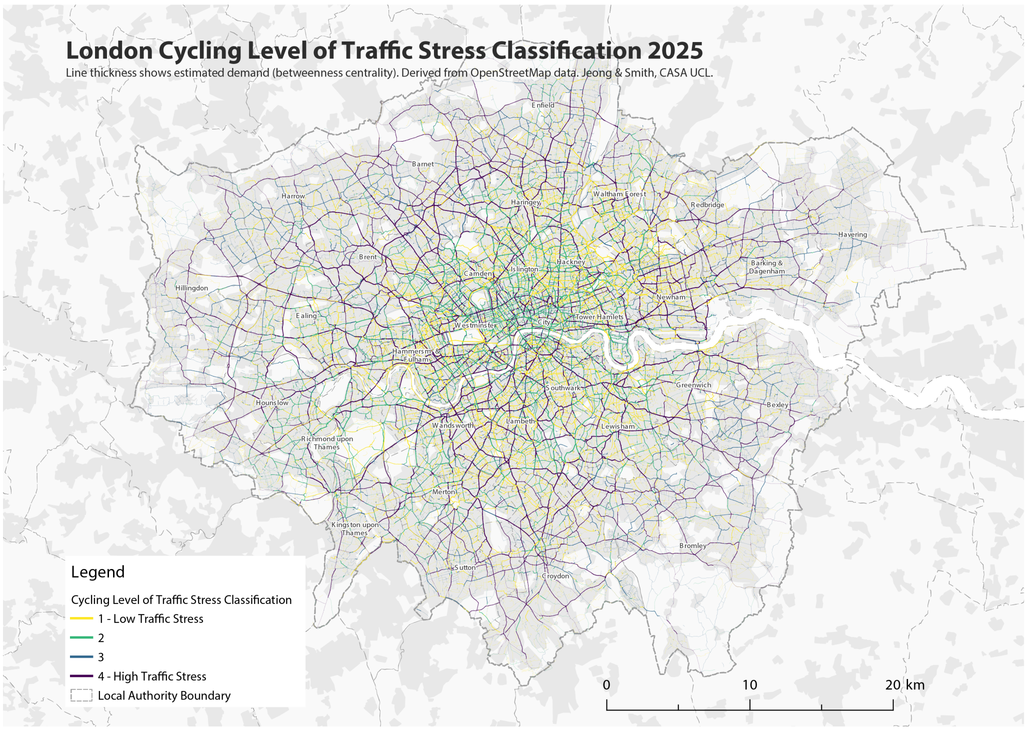


Figure 6: Level of Traffic Stress of all roads in Greater London

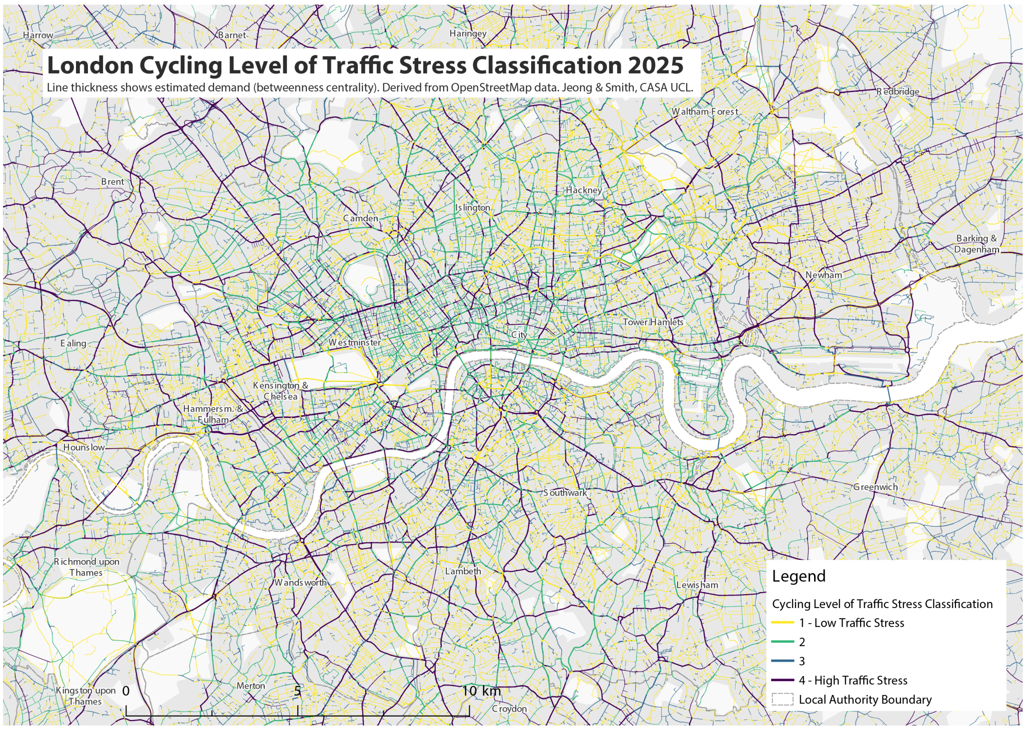


Figure 7: Level of Traffic Stress of all roads in Inner London

4.1.2 Level of Traffic Stress Classification for Greater London

The second classification is Level of Traffic Stress, which includes a wider set of factors influencing cycle accessibility, such as road type, traffic speed and number of carriageways. The LTS classification covers all roads, whether cycle infrastructure is present or not. Level of Traffic Stress is mapped for Greater London in Figures 6 and 7, with line thickness representing link centrality, so that higher demand links are more prominent in the maps. There is a greater contrast between Inner and Outer London with the LTS classification. Inner London has a higher prevalence of less stressful LTS 1 and LTS 2 routes, reflecting lower road speeds and more cycle-friendly conditions in general. There are however several major high-stress Inner London roads identifiable such as Euston Road and Edgware Road. Outer London is characterised with high-stress main roads and arterial roads with LTS 4, while lower stress routes are generally restricted to low centrality residential streets. Again, the overall London picture is fragmented, with low-stress links often intersected or constrained by major high-stress corridors, which likely limits safe and continuous cycling routes across neighbourhoods. This contrast highlights the uneven cycling experience between quieter local roads and the heavily trafficked main routes that form barriers to continuous, safe cycling across the city.

Next, we repeat the borough level indicator calculation for the Level of Traffic Stress classification, again using a centrality-weighted measure, as shown in Figure 8. There is a much clearer split between Inner and Outer London boroughs in this measure, with seven of the top ten boroughs being in Inner London – led by Hackney, Lewisham and Islington – and the bottom 13 boroughs all being in Outer London. The LTS results are very different to the earlier cycle classification results, reflecting the importance of more general cycling conditions, such as road speed and type. The proportions of LTS 1 (fully protected cycle lanes) are relatively consistent between boroughs, coming in around 25% of centrality-weighted roads. Differences in the proportions of LTS 2 and LTS 3 roads are larger, due to the presence of more stressful, higher speed main roads in Outer London, outside of the relatively sparse segregated cycle network. Boroughs that have pursued the Low Traffic Neighbourhood and Quietway approaches, such as Hackney and Islington, score very well in the LTS classification as this measure favours low speed cycling conditions.

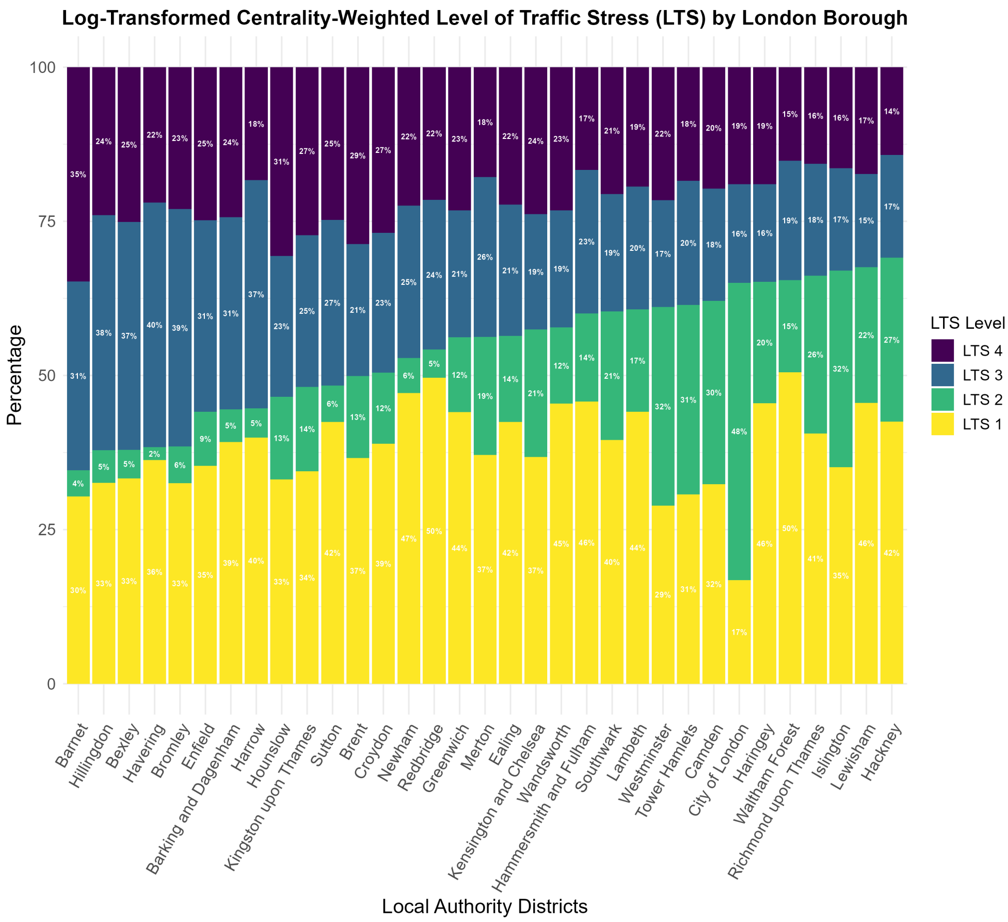


Figure 8: Proportion of centrality-weighted Level of Traffic Stress across Greater London boroughs, ordered by low-stress roads (sum of LTS 1 & 2)

4.1.3 Centrality-weighted Average Cycle Accessibility Score

In this section, the results of the cycle infrastructure classification and the Level of Traffic Stress classification are combined to produce an overall cycle accessibility score, using the methodology described earlier in Section 3.5. The most straightforward way to convert the link-based cycle accessibility scores into an area-based cycle accessibility indicator for local authorities is to calculate the average score. This is computed by normalising the length of each road segment by its cycle accessibility weight. To account for the strategic importance of each segment within wider network, this value is then multiplied by log-transformed centrality. Each road segment is then aggregated by borough, and the average cycle accessibility score per borough is calculated. Lower scores indicate better cycle accessibility. This approach allows for a more accurate representation of cycle accessibility, reflecting not only infrastructure quality but also network connectivity.

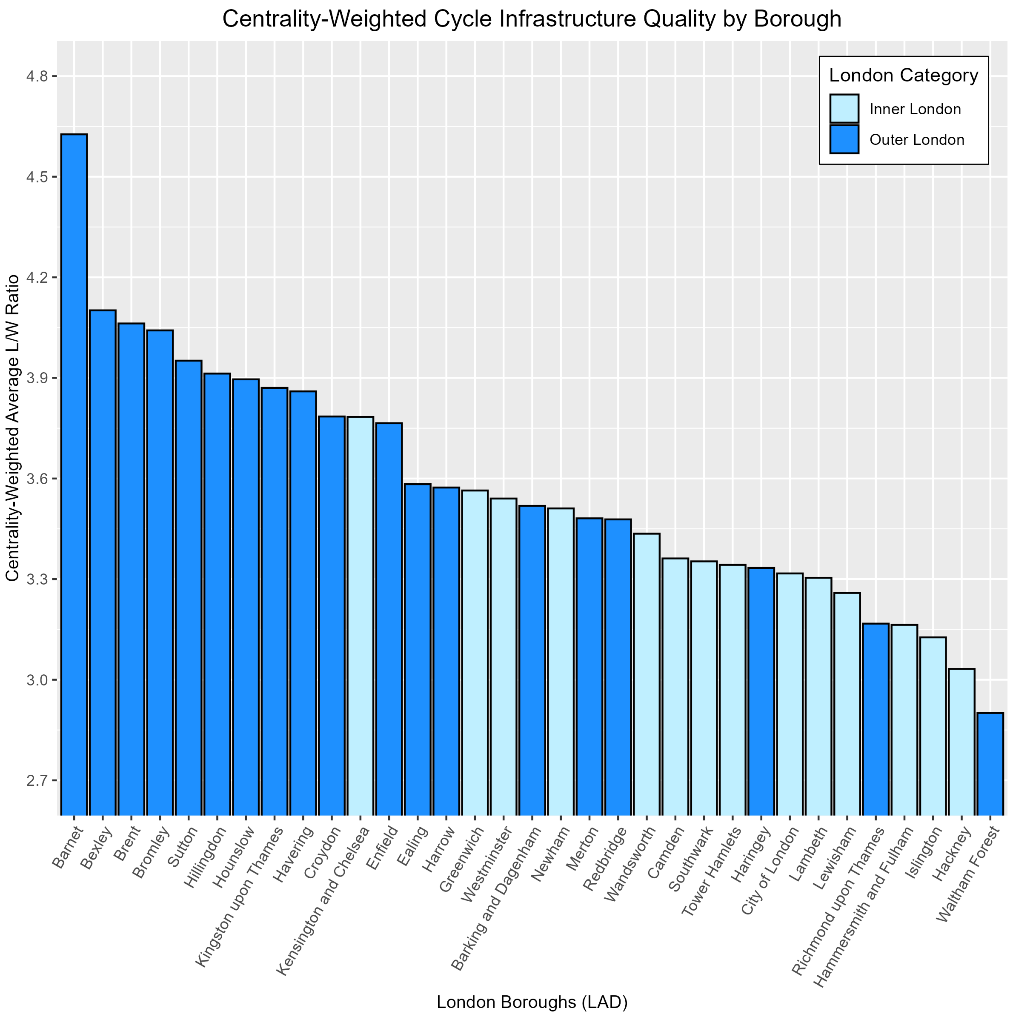


Figure 9: Centrality-weighted average cycle accessibility score aggregated by borough

Figure 9 illustrates that Inner London generally has better cycle accessibility, with leading boroughs such as Hackney, Islington, and Hammersmith. Outer London shows much more variability: while many boroughs rank lower, Waltham Forest scores the highest, and Richmond ranks fourth, standing out as cycle-friendly Outer London boroughs.

Table 3 confirms the earlier results of the cycle infrastructure and LTS classifications. The Cycle Infrastructure results are more favourable to Outer London boroughs, particularly those who have pursued wider segregated networks and have extensive greenspace and rivers/canals. The LTS results favour Inner London boroughs much more strongly, with lower speed roads and Low Traffic Neighbourhood areas scoring well. The overall cycle accessibility score ranking reflects the combination of these two classifications.

Rank	Cycle Infrastructure Ranking	Level of Traffic Stress Ranking	Overall Cycle Accessibility Score Ranking
1	Waltham Forest	Hackney	Waltham Forest
2	Richmond	Lewisham	Hackney
3	Hounslow	Islington	Islington
4	Newham	Richmond	Hammersmith
5	Enfield	Waltham Forest	Richmond
6	City of London	Haringey	Lewisham
7	Redbridge	City of London	Lambeth
8	Greenwich	Camden	City of London
9	Hillingdon	Tower Hamlets	Haringey
10	Hackney	Westminster	Tower Hamlets
11	Tower Hamlets	Lambeth	Southwark
12	Southwark	Southwark	Camden
13	Barking	Hammersmith	Wandsworth
14	Merton	Wandsworth	Redbridge
15	Ealing	Kensington	Merton
16	Kingston	Ealing	Newham
17	Haringey	Merton	Barking
18	Havering	Greenwich	Westminster
19	Hammersmith	Redbridge	Greenwich
20	Lewisham	Newham	Harrow
21	Westminster	Croydon	Ealing
22	Wandsworth	Brent	Enfield
23	Bexley	Sutton	Kensington
24	Camden	Kingston	Croydon
25	Sutton	Hounslow	Havering
26	Islington	Harrow	Kingston
27	Croydon	Barking	Hounslow
28	Bromley	Enfield	Hillingdon
29	Harrow	Bromley	Sutton
30	Barnet	Havering	Bromley
31	Brent	Bexley	Brent
32	Lambeth	Hillingdon	Bexley
33	Kensington	Barnet	Barnet

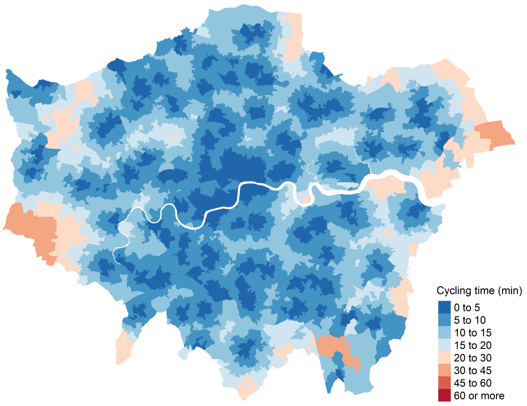
Table 3: London borough ranking by cycle classifications. Higher ranks indicate more accessible cycling conditions. Outer London boroughs are shaded in light grey for clarity.

4.2 Cycle Network Routing and Accessibility Analysis

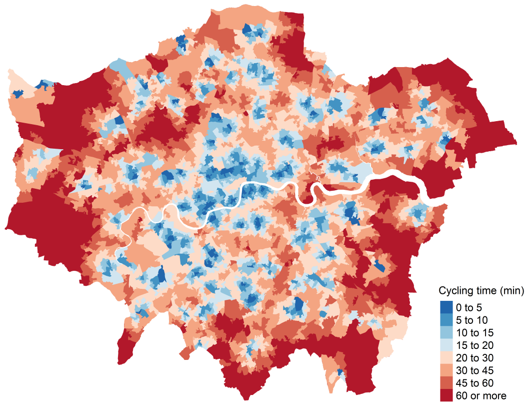
In this section we switch to measuring cycle routes to services and amenities on the cycle network derived in the previous section. We focus particularly on the differences between direct cycle routes – which often require mixing with traffic – and safer routes for vulnerable/inexperienced cyclists that avoid more dangerous roads. Comprehensive inclusive cycle networks would minimise the differences in accessibility between these groups.

4.2.1 Network Routing 15 Minute City Analysis of Cycle Networks

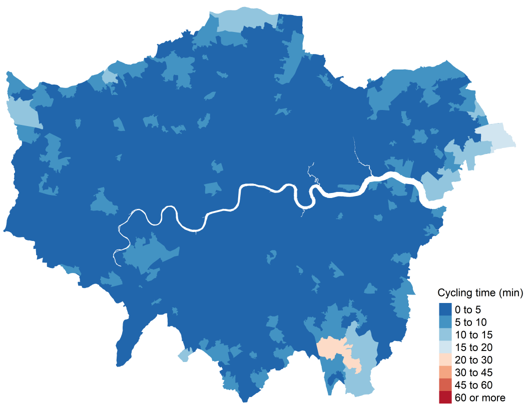
Cycle accessibility is generally strong in high density urban areas, but it varies considerably by the type of destination. Cycle times to the nearest hospital – a relatively sparse destination type – and to the nearest supermarket – a widespread destination type – are shown in Figure 10, using the census geography of LSOAs. Cycling times by direct routes are shown in Figure 10a and 10c, demonstrating that London is very close to the 15 Minute City ideal for experienced cyclists for both



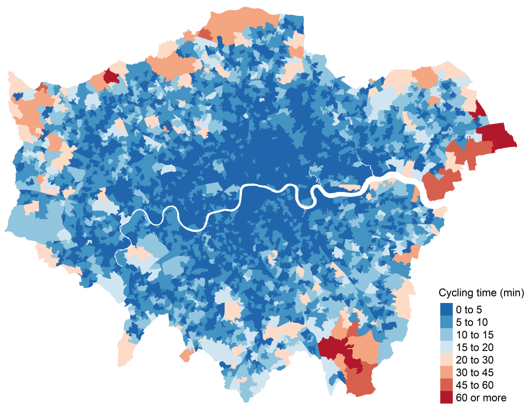
(a) Absolute cycling time to nearest hospital using direct routes



(b) Absolute cycling time to nearest hospital using safer routes



(c) Absolute cycling time to nearest supermarket using direct routes



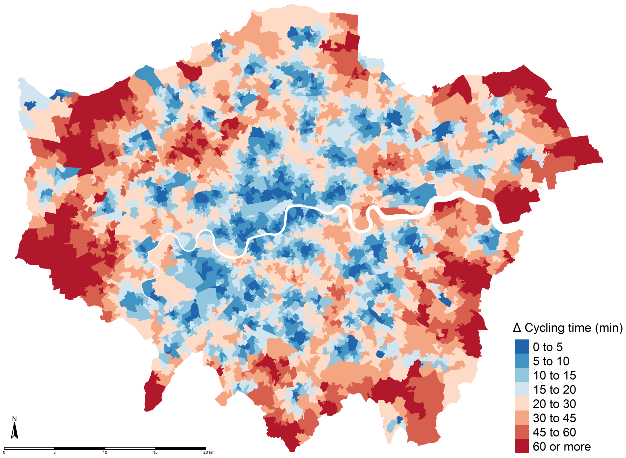
(d) Absolute cycling time to nearest supermarket using safer routes

Figure 10: Absolute cycling time to nearest key amenities using direct (unweighted) and safer (weighted) routes

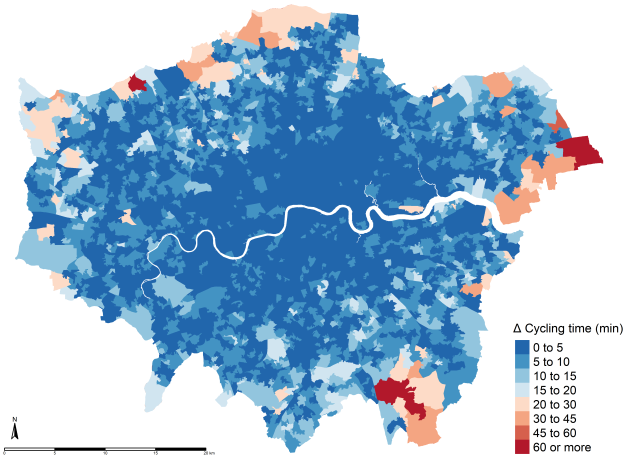
destination types. Whereas for the safer routes cycling accessibility, there is a very large contrast between the supermarket map (10d), which is overwhelmingly accessible within 15 minutes, and the hospital map (10b), where much of the city has cycling times closer to an hour, particularly in Outer London.

These differences between the direct and safer routes are mapped directly in Figure 11, again emphasising the larger differences for the sparser destination type of hospital. The differences between the direct and safer cycle routes are illustrated in more detail in Figure 12 with an example of routes from one particular LSOA origin. We can see that safer routes include taking alternative quieter roads, or even choosing an alternative more distant destination option that can be reached through a safer route.

The overall accessibility to different types of destination by direct and safer cycle routes is summarised in the cumulative plot in Figure 13. This shows the proportion of LSOAs (effectively the proportion of the population) that can reach different facilities at different travel times. We can see in the supermarket example that 100% of LSOAs can reach a supermarket in 15 minutes using direct cycle routes, compared to 90% of LSOAs using safer cycle routes. For Post Offices, these figures are 99% by direct cycle routes and 65% by safer cycle routes. When destinations are sparser, the differences become much greater. For hospitals, 80% of LSOAs can reach a hospital by direct cycling routes compared to only 20% by safer routes. For universities, 50% by direct routes and only 10% by safer routes. These results emphasise how inconsistent infrastructure provision in many parts of London limits safer cycling routes to destinations, particularly for sparser destination types.



(a) Difference in cycling time to nearest hospital



(b) Difference in cycling time to nearest supermarket

Figure 11: Difference in cycling times between direct and safer routes to access nearest hospital and supermarket

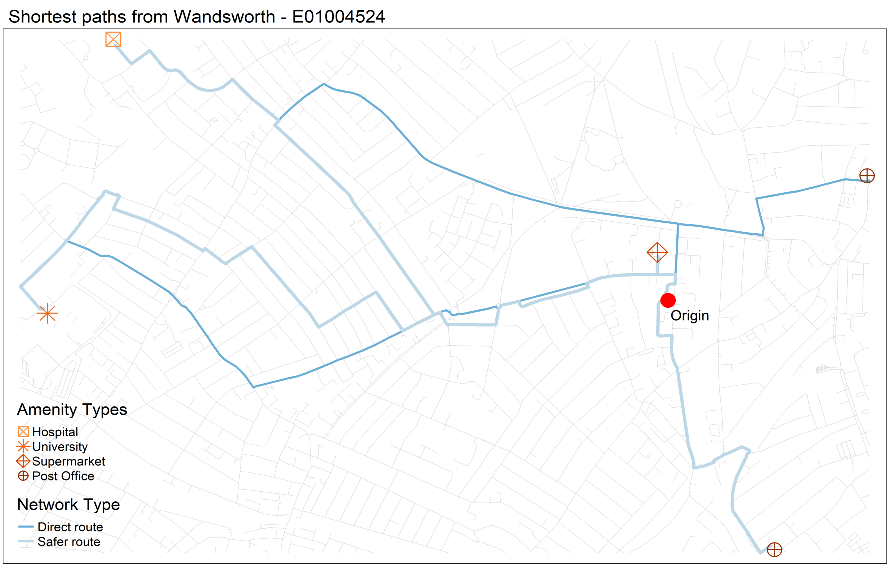


Figure 12: Example shortest paths to access key amenities from an LSOA in Wandsworth (E01004524) using safer and direct routes

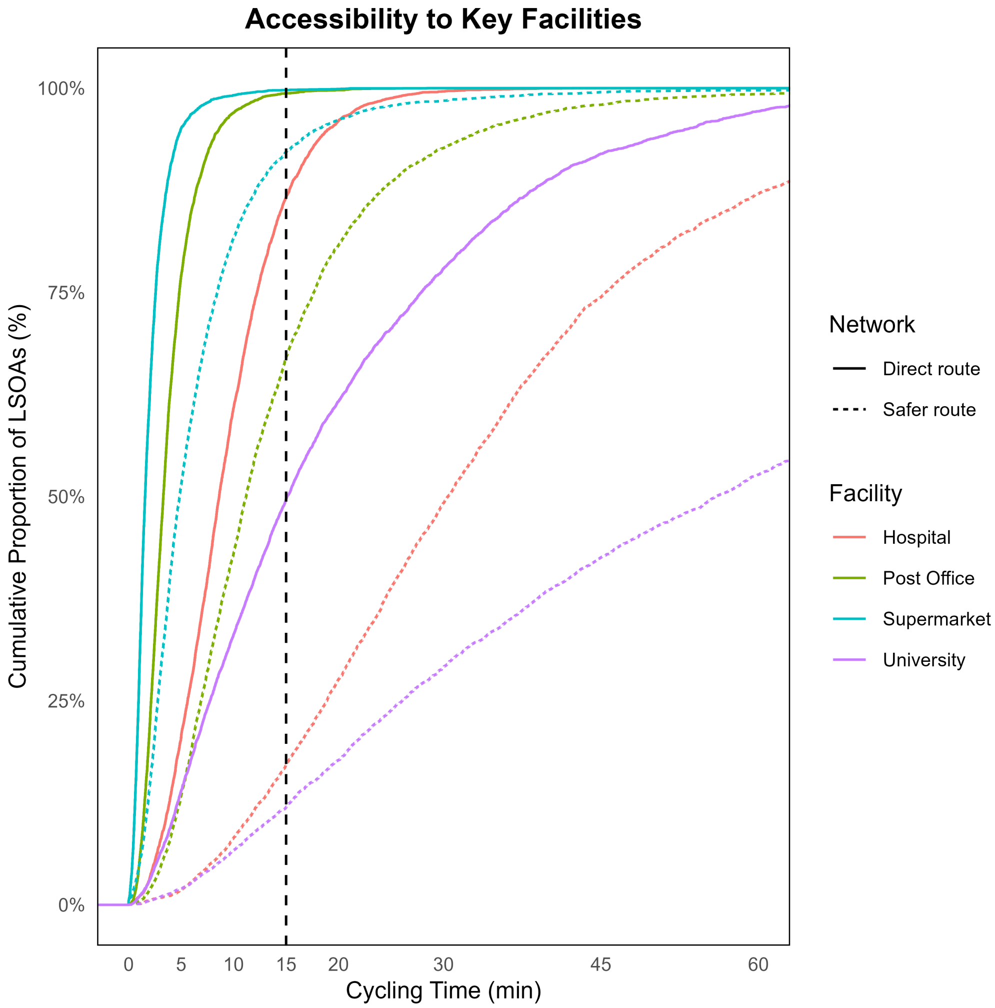


Figure 13: Cumulative plot of cycling accessibility to key amenities using direct and safer routes. Vertical dashed line indicates a 15-minute cut-off

4.3 Validation of Cycle Accessibility Measures Against Travel Behaviour Data

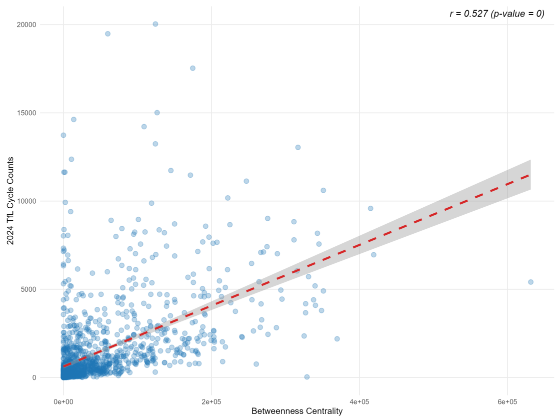
We would expect the cycle accessibility measures developed to correlate with observed cycling behaviour. Betweenness centrality has been used as a proxy for cycling demand and therefore should correlate with observed cycling flows. The cycle infrastructure and Level of Traffic Stress measures would also be expected to correlate with observed cycling behaviour, though this is complicated by self-selection processes in who chooses to cycle. London's cycling demographic tends towards more experienced cyclists, and more vulnerable users may choose not to cycle due to the absence of safer routes. In this section, we present three validation approaches. By leveraging various cycle flow datasets, we validate link-level scores and area-based indicators using a correlation analysis in Section 4.3.1 and 4.3.2, respectively, followed by a linear regression modelling between cycle accessibility measure and travel behaviour in Section 4.3.3.

4.3.1 Link-Level Validation Against TfL Cycle Count Data

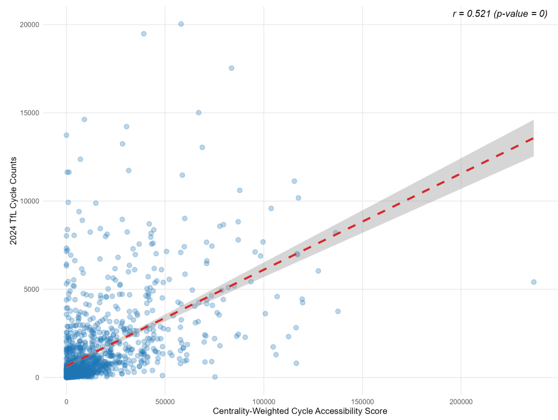
The link-level validation aims to assess the extent to which the proposed link-level weighting scores – including betweenness centrality, cycle infrastructure score, Level of Traffic (LTS) score, and the composite cycle accessibility score – reflect actual cycling activity observed on the network. Although the monitoring sites represent a limited sample relative to the full cycle network, they provide valuable and representative measurement across different areas and road types in London.

The cycle monitoring sites were projected onto the nearest road segments and daily cycle flows were computed for each location. Then, the road network was filtered to only retain 1,451 links containing monitoring stations, each with corresponding daily counts, betweenness centrality, and infrastructure/LTS/accessibility scores. These scores were then multiplied by raw betweenness centrality and validated against daily cycle counts. Figure 14 presents the link-level validations against 2024 TfL cycle count data. All link-level validations show moderately positive correlations with r values ranging between 0.465 and 0.527. The edge centrality shows the highest correlation of 0.527 (see Figure 14a) while LTS shows the lowest of 0.465 (see Figure 14d). In Figure 14c, the vertical line on the left indicates that many of the monitored roads lacked dedicated cycle infrastructure, as shown by the weighted cycle coefficient of 0, yet were still used by cyclists.

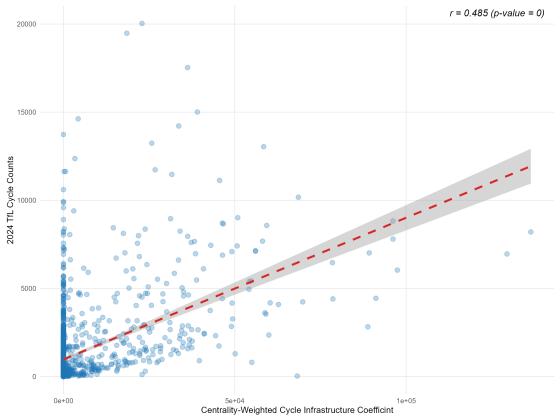
Overall, the link-level validation shows that the centrality measure is providing a reasonable indicator of cycling demand, though it could be improved. The fact that the cycle accessibility score correlations are similar to the centrality correlation does imply that the current cycling demographic in London appears to be more experienced cyclists who are willing to use routes without cycling infrastructure.



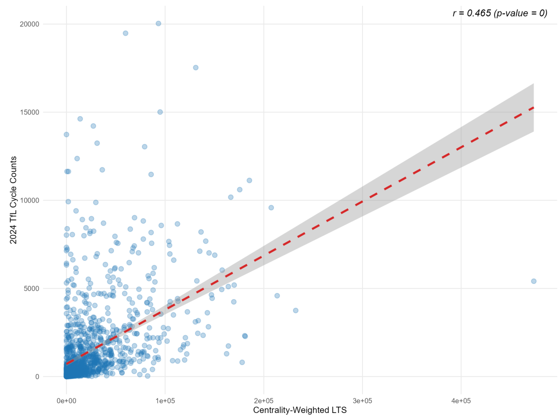
(a) Correlation plot between edge betweenness centrality and link-level cycle counts



(b) Correlation plot between centrality-weighted cycle accessibility score and link-level cycle counts



(c) Correlation plot between centrality-weighted cycle infrastructure score and link-level cycle counts



(d) Correlation plot between centrality-weighted LTS score and link-level cycle counts

Figure 14: Link-level validation against TfL cycle count data

4.3.2 Borough-Level Validation Against Travel Survey Datasets

In this section, we present area-level validation against cycling share at the local authority level. The link-level scores – such as cycle infrastructure, Level of Traffic Stress (LTS), and cycle accessibility scores – were aggregated into area-based measures. This area-based validation captures broader patterns of cycling behaviour and complements the limited coverage of link-level validation by assessing performance at a broad spatial scale.

The centrality-weighted proportions of each cycle infrastructure type and LTS category, as calculated in Sections 4.1.1 and 4.1.2, were further combined to generate a single composite indicator for each borough. For cycle infrastructure, the proportion of each type was multiplied by its corresponding cycle coefficient in Table 2, reflecting its relative contribution to favourable cycling conditions. Similarly, for LTS, the proportion of roads in each stress category was multiplied by a weight (ranging between 0.25 and 1) reflecting lower stress preference, with higher weights assigned to lower-stress roads. The weighted values were then summed across all types to produce a single borough-level measure, where higher values indicate better cycling conditions. However, unlike LTS, which covers the entire road network, cycle infrastructure represents only a subset of roads. To account for this partial coverage and ensure comparability between boroughs, the resulting weighted infrastructure score was further scaled by the overall infrastructure coverage within each borough. This adjustment allows areas with greater infrastructure provision to be appropriately reflected in the final indicator. The centrality-weighted cycle accessibility measure, described in Section 4.1.3, differs in that it combines cycle infrastructure and LTS scores at the link level and normalises each road segment by its cycle accessibility weight, multiplying by log-transformed centrality before aggregation. Unlike the composite indicators for infrastructure and LTS, lower values of the accessibility measure indicate better cycling conditions; therefore, the measure was inverted to facilitate easy comparison across metrics and datasets. Together, these three metrics – centrality-weighted cycle infrastructure, LTS, and inverted cycle accessibility – provide complementary perspectives on cycling conditions across boroughs and were used for correlation analysis against three cycle flow datasets.

Table 4 presents the correlations between borough-level indicators and observed cycling datasets. Correlation strength varies depending on both the type of indicator and the dataset. Across all measures, the highest correlations are observed with the 2021 cycle commuting dataset for trips under 10 km, followed by the Active Lives survey and the 2011 journey-to-work data. The coefficients of cycle accessibility and LTS measures are very similar, showing generally moderate to strong positive correlations. Slightly higher correlations for accessibility measure than LTS measure might indicate that it captures some additional nuance beyond the road stress, such as the contribution of cycle infrastructure. In contrast, the cycle infrastructure measure exhibits consistently lower correlations. The difference may reflect the nature of the datasets: for commuting trips, cycle infrastructure alone may be less critical, whereas physical road conditions often play a greater role.

	Cycle Accessibility Measure	Cycle Infrastructure Measure	LTS Measure
2011 Cycle Commuting	0.6406	0.1352	0.6524
2021 Cycling Commuting (<10km)	0.7031	0.2414	0.6653
2024 Active Lives Survey	0.6721	0.1191	0.6589

Table 4: Correlation of cycle accessibility measure with cycle flow datasets

4.3.3 Relationship between Cycle Accessibility Measure and Travel Behaviour

If cycle infrastructure is a significant barrier to cycling uptake in UK, then we would expect that the cycle accessibility measure to be associated with higher rates of cycling. We performed ordinary least squares (OLS) regression to explore the relationship between cycling behaviour and the cycle accessibility measure. The dependent variable was the proportion of cycle-to-work trips under 10km from 2021 census, representing the local authority-level cycling mode share. The independent variable was the centrality-weighted average cycle accessibility measure, presented in Section 4.1.3.

As shown in Table 5, both the intercept and the cycle accessibility measure are statistically significant predictors of cycling share (p-value < 0.001). The coefficient for the cycle accessibility measure of 8.62 indicates that a one-unit increase in the measure is associated with an 8.62 percentage point decrease in cycling share. This negative relationship aligns with expectations, as lower values of cycle accessibility measure indicate better cycling conditions-reflecting shorter, safer and more connected routes-which in turn support higher cycling uptake. The model yields an adjusted R^2 of 0.48, indicating that about 48% of the variance in borough-level cycling share is explained by the accessibility measure. This suggests a moderately strong relationship, particularly given the complexity of cycling behaviour, with important factors such as demographics not included in this model.

Figure 15 shows interesting patterns in the model residuals. Many Inner London boroughs exhibit higher cycling shares beyond their infrastructure provision, with Hackney recording the highest cycling share. In contrast, many Outer London boroughs fall below the regression line, indicating lower cycling uptake than expected based on their infrastructure. These boroughs are typically located farther from major employment locations, which likely restricts cycling due to longer commuting distances.

Parameter	Coefficient	Std. Error	*T-statistics*	*P-value*
Intercept	37.736	5.627	6.706	1.68e-07
Cycle Accessibility Measure	-8.620	1.566	-5.505	5.05e-06
R^2	0.49			
Adjusted R^2	0.48			
RMSE	3.13			

Table 5: The results of ordinary least squares (OLS) model between cycling mode share and cycle accessibility measure. Model performance is assessed using adjusted R^2 and RMSE.

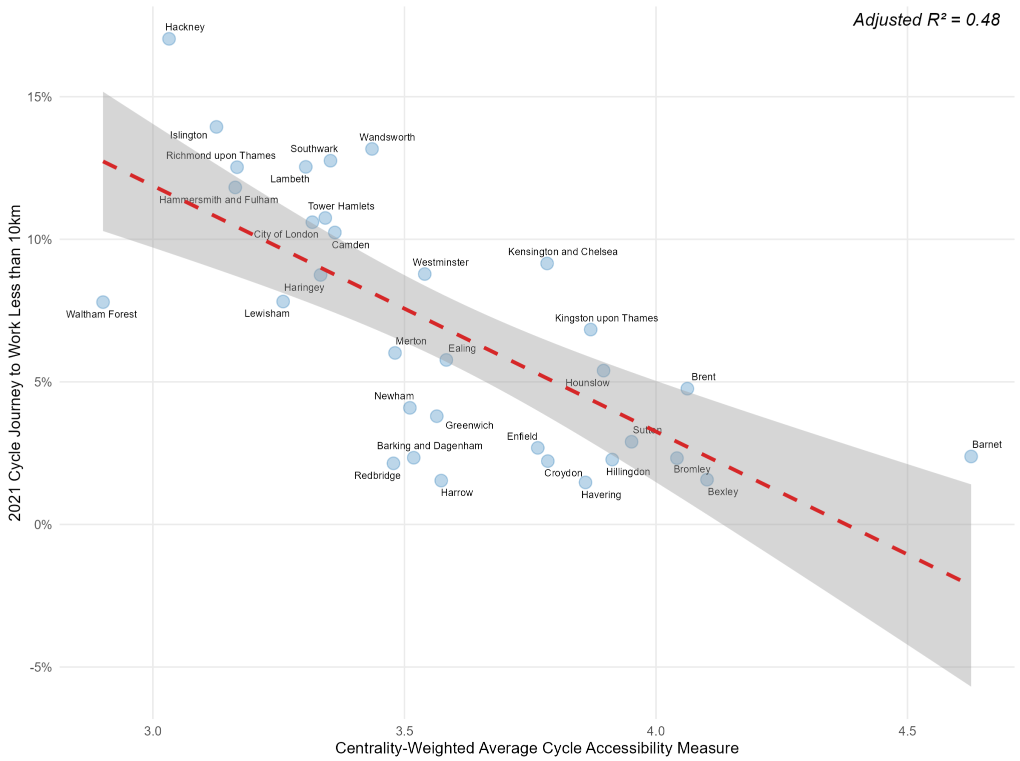


Figure 15: Linear regression of 2021 cycling commuting less than 10km on centrality-weighted average cycle accessibility scores aggregated by borough

5 Discussion

5.1 Cycle infrastructure and accessibility indicators for policy implementation

This research has developed detailed cycle infrastructure and accessibility measures, through mapping and summary statistics at the local authority level. The cycle infrastructure classification captured the generally inconsistent and fragmented distribution of London's cycle network, with limited provision of protected cycle lanes separated from road traffic. The most comprehensive protected cycle networks were found in Waltham Forest and Richmond-upon-Thames, both in Outer London, reflecting sustained pro-cycling investment to improve cycling facilities and achieving the highest rates of protected cycle lane provision. Inner London boroughs known as being cycle-friendly, such as Hackney and Islington, did not score as well as expected with the infrastructure measure, due to their reliance low speed shared infrastructure approaches, such as Low Traffic Neighbourhoods. The weakest provision was found in car-dependent Outer London boroughs, such as Barnet and Bexley, and Inner London boroughs that have politically resisted cycle lane development, such as Kensington and Chelsea.

The second Level of Traffic Stress classification provides a broader perspective on road conditions and safety, and produced contrasting results to the cycle infrastructure classification. In this measure, lower-speed Inner London boroughs performed well due to less stressful cycling conditions. Cycle-friendly Inner London boroughs, including Hackney, Lewisham and Islington, have the best results in London, with this measure capturing the benefits of Low Traffic Neighbourhoods, Quietways and early adoption of the 20mph speed limit, where low speed has been prioritised over full separation of infrastructure. Richmond and Waltham Forest also score well with this measure, but these are effectively outliers as Outer London in general features much more stressful conditions for cycling. In general, major roads are typically high-stress roads and fragment lower-stress neighbourhoods, limiting the potential for safe and continuous longer distance cycling. In this context, LTS values assigned to individual road segments are particularly valuable for prioritising interventions, enabling improvements to be targeted towards roads where upgrades would have the greatest network-wide impact. In London, where high-stress roads often serve key connectors in the cycle network, such an approach can help authorities move beyond borough-level summaries to focus on corridor-level or even neighbourhood-level upgrades.

The cycle accessibility score, which combines cycling safety with the quality and connectivity of detailed cycle infrastructure, provides an overall representation of cycling accessibility across Greater London. The striking Inner-Outer London divide shown in Figure 9 reveals a clear spatial discrepancy: in many Outer London boroughs, accessible cycle infrastructure is often limited, potentially constraining local trips. Waltham Forest and Richmond are the exceptions, with Haringey also performing relatively well. These results underscore the value of the measures developed as a diagnostic and monitoring tool for local authorities, helping them track and evaluate their cycle networks and develop data-informed policies that deliver high-quality, safe and inclusive cycling environments.

5.2 Cycling accessibility to 15 Minute City urban functions

The network routing analysis highlights how cycling accessibility varies by destination type and between direct and safer cycling routes. Using direct routes, widespread destinations such as supermarkets and post offices are easily reachable across Greater London with 10-15 minutes, while less common destinations such as hospitals were typically reachable within 30 minutes travel. Cycling accessibility was however much weaker for cyclists prioritising safer routes. Although widespread destinations such as supermarkets remain broadly accessible with only modest increases in travel time, access to more sparsely distributed destinations is substantially reduced. For example, 80% of LSOAs could reach a hospital in 15 minutes direct cycle time, but only 20% of LSOAs could reach a hospital in 15 minutes by safer cycle routes. This represents a major accessibility disadvantage for inexperienced and more vulnerable cyclists, underscoring the limitations of London's current cycle network in supporting equitable access to essential services, and limiting the expansion of cyclists for currently underrepresented demographics.

In Inner London, the combination of dense urban form and greater investment in cycling facilities means that even vulnerable cyclists can usually access most everyday services within 15 minutes. By contrast, in Outer London, where facilities are more dispersed and high-stress roads are prevalent, safer routes are often circuitous or unavailable, leaving many residents effectively excluded from accessing key services by bike. This spatial discrepancy raises an important equity concern: while the 15 Minute City ideal appears achievable for confident cyclists, it is far less attainable for inexperienced or vulnerable groups, particularly for sparser services and amenities in suburban settings. The concentration of safer cycling access in central areas therefore reinforces existing inequalities between Inner and Outer London. Addressing this gap requires not only the expansion of safe infrastructure in Outer London (following progress by boroughs such as Waltham Forest and Richmond), and also better alignment of cycling networks with the spatial distribution of essential services.

5.3 Cycling accessibility and cycling uptake

The OLS regression results provide strong evidence that cycle infrastructure plays a significant role in supporting cycling uptake in the UK. Boroughs with higher cycle accessibility scores generally exhibit higher cycling rates, reinforcing the argument that improving infrastructure can help break down barriers to cycling participation.

That said, commuting cycling data may overestimate cycling share in Inner London boroughs because of their proximity to major employment centres. Residents in these areas typically have much shorter commuting distances—conditions that encourage cycling regardless of infrastructure quality. This likely contributes to the cluster of Inner London boroughs performing above model expectations. In contrast, many Outer London boroughs underperform relative to the model's predictions. One likely explanation is that boroughs with fragmented or disconnected networks may achieve moderate scores on borough-level accessibility metrics but still fail to offer continuous, safe routes linking homes to key destinations. The longer average commuting distances in these areas, combined with gaps in network connectivity, may further constrain cycling uptake.

Overall, while infrastructure quality is clearly important, these patterns underline that it interacts with other factors such as trip length, network continuity, local geography and demographics. Addressing underperformance in Outer London will therefore require not only better infrastructure provision but also strategic improvements to route connectivity and integration with land use patterns.

5.4 Limitations

There are various areas where this research could be improved. This research used betweenness centrality as a proxy for the relative importance of each road within the overall cycle network. The centrality values computed here are based solely on the topological structure of the network and therefore may not fully capture functional importance, especially where travel speed, safety, or user preferences influence route choice. Nevertheless, in the absence of comprehensive cycling flow data, betweenness centrality remains a useful indicator. Future work could explore more cognitively oriented metrics, such as angular minimisation, which may better approximate human navigation behaviour.

Due to the absence of preference coefficient specific to physically separated cycle lanes, this research applied the coefficient for mandatory cycle lanes as a proxy. However, given the generally higher preference for protected cycle lanes over painted cycle lanes, this approach is likely to underestimate their relative importance. Future research could address this limitation by calibrating coefficients using empirical mobility data, and by examining how preferences vary across cyclist types (e.g., experienced vs. inexperienced cyclists).

The cycle flow datasets were valuable for validating the link-level weighting scores and area-based indicators against actual cycling behaviours. However, the link-level cycle count data was limited in sample size and area-level cycle flow datasets underrepresent cycling trips for other purposes, many of which are local. This was particularly evident for some Outer London boroughs in Figure 15, where observed values fell below the regression line. Alternative data sources could include travel diary surveys to capture a wider range of trip purposes, though these are often limited in sample size and spatial granularity, or mobile phone data, which could help fill gaps in local and active travel patterns. However, inferring mode choice from mobile data can be challenging and dataset-dependent. Such data could also help validate assumptions made in cycle routing and in the use of betweenness centrality as applied here.

A further limitation of this study relates to potential edge effects at the boundary of Greater London. Since both roads and points of interest were restricted to those located within Greater London, accessibility may have been underestimated for peripheral neighbourhoods. In practice, residents in these areas are likely to access key amenities situated just outside the administrative boundary, meaning that the results may not fully capture their true accessibility.

6 Conclusion

This research has developed a set of cycle infrastructure and accessibility measures designed to support planners and policymakers in evaluating progress towards high-quality, safe, and inclusive cycle networks. By combining an open-source classification of cycle infrastructure with an improved Level of Traffic Stress framework, and by integrating these with network centrality, we have produced a suite of measures that capture infrastructure quality, cycling safety and network connectivity.

Applying these measures to Greater London reveals an inconsistent and sometimes fragmented cycle network, with clear differences between Inner and Outer London, and between boroughs that have pursued highly varied cycle infrastructure policies. The cycle infrastructure classification highlights the role of long-term local authority investment in shaping current provision. The Level of Traffic Stress analysis offered a broader perspective on safety, showing that Inner London has generally safer cycling conditions, consistent with recent speed limit and Low Traffic Neighbourhood policies. High-stress arterial roads continue to form barriers to safe, continuous cycling in both Inner and Outer London. The combined accessibility scores further underscored the divide between Inner and Outer London, with many Outer London boroughs offering limited access to safe and connected infrastructure, though notable exceptions such as Waltham Forest and Richmond demonstrate the positive impact of sustained investment and links between cycle networks and greenspace.

Analysis of routing to urban functions within a 15 Minute City framework revealed how accessibility varies by destination type, and between direct and safer cycle routes. While widespread facilities such as supermarkets remain broadly accessible even on safer routes, access to more sparsely distributed destinations such as hospitals and universities is substantially reduced, particularly for vulnerable cyclists in Outer London. This raises important equity concerns, suggesting that current cycling conditions are suitable for confident and experienced cyclists while leaving many others excluded from safe and convenient access to key services.

Finally, the positive relationship between cycle accessibility measures and cycling uptake reinforces the central role of infrastructure in supporting cycling participation. At the same time, the results highlight the interaction between infrastructure and other factors such as trip length, network continuity, and land use, particularly in Outer London where longer journeys and fragmented networks constrain cycling potential. Taken together, these findings underscore the value of detailed, open-source infrastructure and accessibility measures as diagnostic and monitoring tools for local authorities. They can help track progress, identify gaps, and support the development of more equitable and inclusive cycling policies. Realising the vision of a high-quality, city-wide cycle network in London will require not only continued investment in protected infrastructure but also targeted interventions to improve connectivity across high-stress corridors and better alignment of cycling networks with the distribution of essential services.

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