Active Mobility Accessibility Index – Assessing Local Transport Competitiveness

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Abstract

Active Mobility Accessibility Index (AMAI) quantifies the competitiveness of walking and cycling relative to driving using travel-time and distance ratios on identical sampled origin-destination pairs, reflecting network structure rather than destination choice. AMAI combines time parity and distance parity in a simple diagnostic score, using equal weights as a default specification for interpretation and policy use. Applied across the five Tyne and Wear local authorities, it demonstrates that cycling is more competitive than walking against driving. The median origin-level cycling AMAI is 0.820 and the median walking AMAI is 0.645. Parity remains limited where the share of origins at or above parity is 10.0% for cycling and 1.7% for walking. Initial API-based tests suggested that time-of-day effects are limited for the short local trips studied here, supporting development of a scalable in-house routing workflow for the main analysis. Validation against OA-level Census 2021 mode shares, with controls for terrain gradient and commute-distance composition, suggests that AMAI captures a relevant behavioural signal, while its main value lies in diagnosing local network competitiveness for policy and planning.

1. Introduction

Cities increasingly recognise cycling and walking as affordable, healthy, low-emission modes, yet policy still lacks clear multimodal measures of their competitiveness. In the UK, Gear Change (Department for Transport, 2020) and establishment of Active Travel England increased demand for objective local-scale indicators, while many existing measures still treat modes separately and therefore miss structural biases between active travel and driving. AMAI addresses that gap and supports equity assessment. Car-centric design disadvantages people who rely on walking, cycling, or public transport through severance, indirect routes, unsafe crossings, and traffic conditions. Existing accessibility metrics usually measure reach or cost, not modal competitiveness. AMAI instead treats accessibility as a comparative property, quantifying how network structure affects active travel relative to driving (Figure 1).

Applied to existing transport systems, AMAI supports consistent multimodal evaluation across scales and provides a clear parity threshold for identifying where active modes are already competitive. It can distinguish areas suited to behaviour change, safety, or maintenance measures from areas that require structural intervention, and it can be used prospectively to test proposed changes. This paper's contributions are: (1) a mode-parity accessibility index combining travel time and directness in a simple, interpretable diagnostic score; (2) a directionally balanced origin-destination sampling design for local trips; and (3) a policy-relevant framework for benchmarking active travel competitiveness, identifying structural deficits, and informing intervention prioritisation. The remainder of this paper defines AMAI and the origin-destination sampling protocol, then reports results for the North East England case study, followed by discussion about interpretation, limitations and use-cases.

2. Related Work

Review of measures of walking and cycling accessibility by (Vale et al., 2015) developed a typology of metrics – based on distances, land-use and utility. (Owen and Levinson, 2015) introduced a concept of continuous time-weighted accessibility metric which captures the fact that during different times of day, the comparative performance of modes can vary significantly, and that the average, maximum and variance are all factors in personal decision about mode choice. Relation between walking and land use diversity, intersection density, and the number of destinations within walking distance were the strongest explanatory factors in a review by (Ewing and Cervero, 2010). Policy paper by (International Transport Forum, 2019) defines three practical indicators: proximity, accessibility and transport performance, which is a ratio of proximity to accessibility. Work by (Broach et al., 2012) looked in more detail at individual routes cyclists take, and points to a number of characteristics affecting mode choice –turn frequency, slope, intersection control, traffic volumes, availability of off-road paths, traffic calming, with distance being of lesser importance than infrastructure features for commuter cyclists. (Winters et al., 2010) investigated what motivates people to take routes that are longer than shortest path, to discover that preference for cycling infrastructure and safety features makes a 25% longer route acceptable for 90% of cyclists. Analysis of circuity (indirectness) of street network available for driving and walking in 40 American cities by (Boeing, 2017) discovered that, some network topologies of whole cities chronically display features that systematically disadvantage walking. Work by (Giacomin and Levinson, 2015) looked at temporal changes to circuity of 51 metropolitan areas is US and found that between 1990 and 2010 the problem has worsened. (Costa et al., 2021) performed similar analysis is Lisbon, Portugal, to quantify the improvements from expansion of the city's cycling infrastructure. Approach presented in (Lowry et al., 2016) measures accessibility including fixed bicycling stress factors associated with every road, affecting links impedance during route cost calculation. This way they were able not only to estimate accessibility, but also each link's contribution to overall accessibility scores. Proponents of Walk ScoreTM (Carr et al., 2010) apply a multivariate analysis of walking environment and wider socio-economic landscape. AMAI complements such approaches by quantifying mode parity – stress and comfort measures can be layered as constrains or weights. Analysis of physical activity of 6822 adults from 14 cities on five continents (Sallis et al., 2016) showed positive correlation between various socio-technical factors, with, relevant to our work, intersection density being one of the highest scoring. Estimates of costs of driving and benefits of cycling and walking in EU (Gössling et al., 2019) provided monetary values for kilometre driven (€-0.11), cycling (€+0.18) and walking (€+0.37). Reduction in kilometres driven and increase in those walked and cycled can thus result in a measurable economic efficiency. Traditional indicators measure access, cost, circuity, safety, or comfort, but do not usually compare modes on identical origin-destination pairs. Table 1 situates AMAI within this literature: it adds a reproducible mode-parity perspective that compares walking and cycling with driving in both time and distance.

Typology	What it measures	Source
AMAI	Walk/cycle performance relative to car (time + distance parity on same O–D)	This paper
Accessibility typologies (distance / land-use / utility)	Families of walking/cycling accessibility measures; sensitivity to method choices	(Vale et al., 2015)
Continuous time-weighted accessibility	Time-varying accessibility (captures temporal variability)	(Owen and Levinson, 2015)
Built environment correlates (meta-analysis)	How land-use mix, intersections, etc. relate to walking/travel outcomes	(Ewing and Cervero, 2010)
Benchmarking indicators (proximity / accessibility / transport performance)	Practical cross-area indicators; transport performance ratios	(International Transport Forum, 2019)
Circuity / indirectness	Structural detour penalties (walk vs drive; temporal changes; before/after)	(Boeing, 2017, Giacomin and Levinson, 2015, Costa et al., 2021)
Low-stress / comfort-weighted accessibility	Accessibility with stress/comfort embedded in link impedance; link contributions	(Lowry et al., 2016)

Table 1. Positioning of AMAI within selected accessibility and transport-performance typologies reviewed in the literature.

3. Data and Method

The method we present measures how favourable or unfavourable a transport network is to active travel, compared to car travel, with a focus on local trips. Our output is the Active Mobility Accessibility Index (AMAI). Origins are defined by the user and, in our experiments, we used population-weighted centroids of Middle Super Output Areas (MSOA) and Output Areas (OA), a standard sampling convention for urban locations in the United Kingdom.

The study began with an exploratory routing phase using the Google Maps Directions API, including tests across different times of day for short local trips. Those initial tests suggested that time-of-day effects, including congestion-related delay, were limited for the trip distances considered here. Because large-scale API-based routing is costly, the main analysis reported in this paper uses an in-house routing solution built from bulk-downloaded OpenStreetMap data.

In the in-house model, OSM ways are split into directed edges between consecutive nodes, and one-way restrictions are enforced by generating only permitted directions of travel. OSM turn-restriction relations are compiled into forbidden transitions between directed edges, and routing is performed on an edge-based state graph of the form $(node, previous\_edge)$ so that turn restrictions are respected during path search. Travel times are derived from edge lengths and mode-specific speed assumptions. For driving, posted speed limits are used where available and a default of 30 km/h is used otherwise. Default speeds are 4 km/h for walking and 15 km/h for cycling. Nodes tagged $highway = traffic\_signals$ incur delay when passed through, including when the snapped origin or destination node is itself a signal. Road signal delay is set to 15 seconds and off-road walking and cycling signal delay is set to 30 seconds. The current in-house model is static and does not include time-dependent congestion. For each origin (L), we generate destinations at three distances, $D \in 0.5km, 1km, 2km$, corresponding to typical local access. The first distance band corresponds to immediate neighbourhood, 1 km is a tolerance value for a short walking trip, and 2 km is a distance where cycling remains competitive. Using concentric distance bands standardises sampling between urban environments of different densities. Around each origin L and for each distance band D, we attempt to identify K=8 hypothetical destinations. Conceptually, this divides the space around the origin into 8 angular slices (Figure 1). It is a practical compromise between capturing directional structure and computation cost. For each slice, we generate one destination in that direction at distance D. Each destination is denoted $N_i(L, D)$, where i is the slice index. For each origin-destination pair $(L, N_i(L, D))$, we request route information (distance and travel time) for three modes: driving, walking and cycling. All modes are evaluated on the same origin-destination pairs, so differences in results arise only from mode-specific routing constraints and network structure.

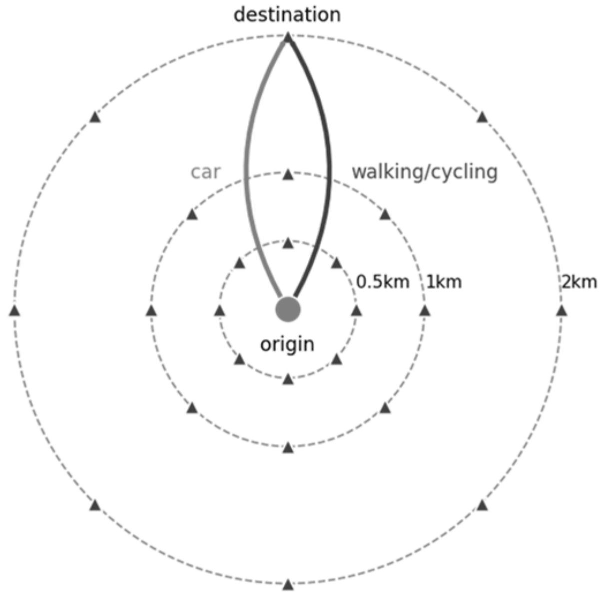

Figure 1. Directionally balanced origin-destination sampling around each origin across three local distance bands.

We evaluate the time it takes for the three modes to travel between each origin-destination pair. We do that by comparing active modes' journey duration to the same trip made by car (Equation 1). That ratio is the first, temporal, component of our index.

$$\mathrm{TP}_m^{(i)} = \frac{T_{\mathrm{car},i}}{T_{m,i}} \tag{1}$$

where $\mathrm{TP}_m^{(i)}$ = time parity ratio for mode m
i = slice (direction) index
$T_{\mathrm{car},i}$ = car travel time (minutes)
$T_{m,i}$ = travel time (minutes) using mode m

We also evaluate how direct the routing is for the three modes. A common barrier to walking and cycling is being forced into detours (e.g., to reach a legal crossing), which do not apply to drivers in the same way. To quantify that we define a distance parity ratio that compares how direct the walking or cycling route is relative to the driving route (Equation 2). This shows accessibility disadvantage and spatial discontinuity of infrastructure, which are invisible if we look only at travel time.

$$\mathrm{DP}_m^{(i)} = \frac{D_{\mathrm{car},i}}{D_{m,i}} \tag{2}$$

where $\mathrm{DP}_m^{(i)}$ = distance parity ratio for mode m
i = slice (direction) index
$D_{\mathrm{car},i}$ = length (km) of the car route
$D_{m,i}$ = length (km) of the route travelled by mode m

To combine both ratios, we define a slice-level score as the simple average of time and distance parity (Equation 3). Equal weighting is retained because it is transparent and easy to interpret, although validation suggests that the time component aligns more strongly with observed mode shares in this dataset.

$$s_m^{(i)} = 0.5 \cdot \mathrm{TP}_m^{(i)} + 0.5 \cdot \mathrm{DP}_m^{(i)} \tag{3}$$

where $s_m^{(i)}$ = slice-level active mobility score for mode m
0.5 = equal weight for time and distance components

We aggregate across directions by taking the median slice score for each origin and distance band (Equation 4), which reduces sensitivity to extreme directions and gives a typical measure of competitiveness around each origin.

$$\mathrm{AMAI}_m(L, D) = \mathrm{median}_{i=1,\dots,K}\, s_m^{(i)} \tag{4}$$

where $\mathrm{AMAI}_m(L, D)$ = Active Mobility Accessibility Index
m = active travel mode (walking or cycling)
L = origin node
D = distance band
K = number of slices

We then take the median across the three distance bands to obtain $\mathrm{AMAI_m(L)}$, and the median across origins to obtain a city-wide indicator for each mode. Alongside this median, we report the share of origins at or above parity (1.0) to show how widely competitiveness is distributed.

AMAI values near 1.0 indicate mode parity where active modes perform similarly to driving for local trips. Higher values indicate an advantage these modes have over car, while lower values signify active travel's disadvantage. Separating components aids in diagnosis further – low DP (distance parity) suggests detours and indirectness, and low TP (time parity) suggests operational constraints (e.g., route may appear direct but with many signalised junctions where pedestrians and cyclists have to wait). The presented method differs from conventional accessibility measures by being ratio-based, comparative, and scale-flexible. Instead of counting reachable destinations or evaluating impedance costs, it focuses on relative efficiency between active travel and driving. It is designed for analysing local trips, using spatially balanced destinations to ensure fairness and consistent sampling. This aspect of our method provides a reflection of structural geometry of the transport network, rather than being biased by effects of land-use or known commute patterns. AMAI produces a clean measure of network multimodal competitiveness and can be used both descriptively, to benchmark existing conditions, and prospectively, to assess how proposed network changes alter active travel competitiveness.

4. Results

4.1 Regional Analysis

The Active Mobility Accessibility Index was applied across the five Tyne and Wear local authorities: Newcastle, Gateshead, North Tyneside, South Tyneside, and Sunderland. The results reported in this section are derived from the in-house Open Street Map-based routing workflow described above.

At the regional distance-band level, median walking AMAI was 0.628 at 500 m, 0.645 at 1 km, and 0.660 at 2 km, while median cycling AMAI was 0.810, 0.820, and 0.824 respectively. At OA level, walking achieved a median AMAI of 0.645 with 1.6% of origins at or above parity, while cycling achieved a median AMAI of 0.820 with 10.1% of origins at or above parity. Figure 2 shows how that parity coverage changes across the three local distance bands. At OA level, parity coverage declines sharply with distance, especially for walking: walking parity falls from 6.3% at 500 m to 2.3% at 1 km and 0.2% at 2 km, while cycling falls from 19.9% to 13.2% and 5.1% over the same bands.

After aggregation by local authority, cycling medians ranged from 0.788 in Sunderland to 0.845 in Newcastle upon Tyne and cycling parity shares ranged from 5.6% in Sunderland to 14.7% in North Tyneside. Walking medians ranged from 0.622 in Sunderland to 0.662 in Newcastle upon Tyne and walking parity shares ranged from 0.8% in Sunderland to 2.5% in North Tyneside. Overall, the regional results show that distance parity is generally closer to or above parity while time parity is materially lower. Regional median walking time and distance components are 0.135 and 1.155, and regional median cycling time and distance components are 0.500 and 1.144. This indicates that relative speed difference, operational delay and weak priority matter more than route directness alone. From a policy perspective, Newcastle upon Tyne and North Tyneside appear to offer more latent potential for mode shift where active modes are already relatively competitive, while Sunderland indicates more persistent structural deficits in connectivity, directness, or priority that are more likely to require network intervention.

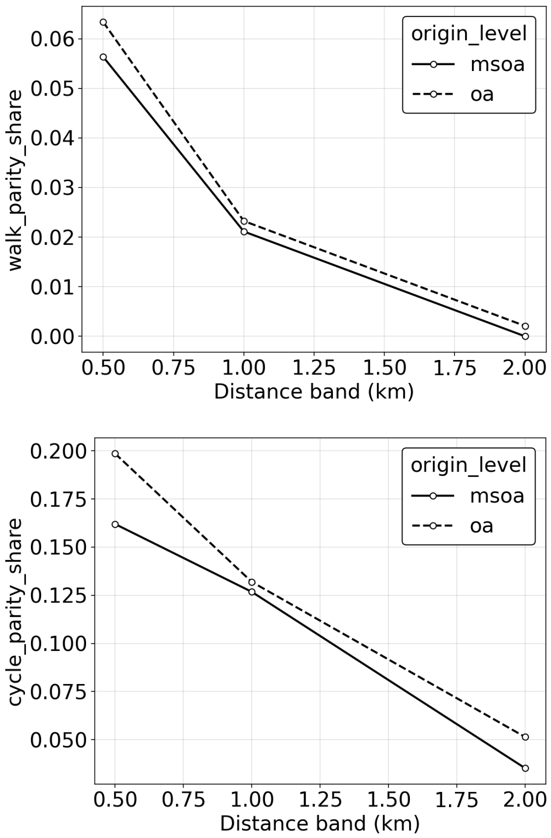

Figure 2. Share of origins at or above parity by distance band. The top panel shows walking and the bottom panel cycling. Parity declines with distance for both modes, but the drop is much steeper for walking.

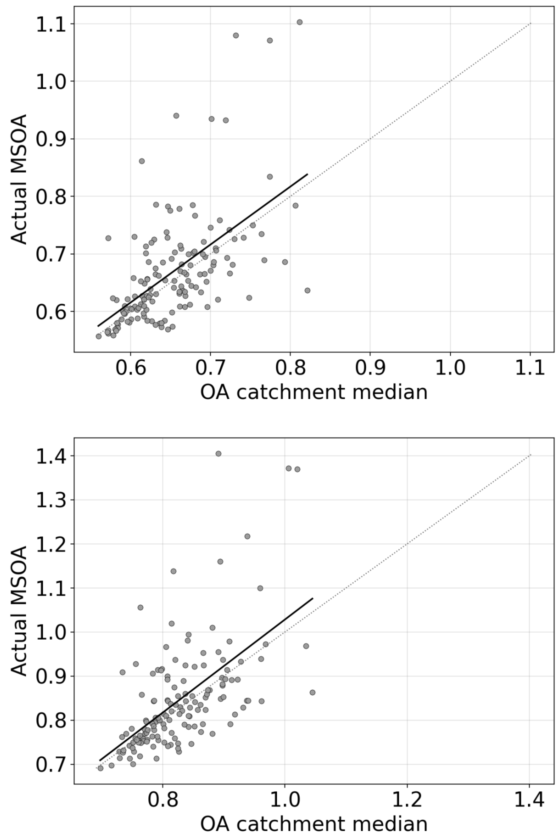

Figure 3. Consistency between actual MSOA values and OA-catchment medians. The top panel shows walking and the bottom panel cycling. Agreement is moderate to strong, while the spread around the fitted relationship indicates meaningful neighbourhood-scale variation within MSOA geography.

4.2 Comparison Between MSOA and OA Levels

To assess how the method behaves across planning scales, we compared actual MSOA values with the median OA values inside MSOA catchments across Tyne and Wear.

For overall cycling AMAI, the correlation between actual MSOA values and OA-catchment medians was 0.587 using Pearson’s r and 0.635 using Spearman’s rank correlation, with both $p < 0.001$, indicating that the relationship is very unlikely to be due to chance alone. Here, the OA-catchment median means the median OA value among all OAs assigned to a given MSOA catchment, while Pearson’s r measures linear agreement and Spearman’s coefficient measures whether the rank order is preserved even if the relationship is not perfectly linear. The mean absolute error (MAE), which is the average absolute mismatch between the actual MSOA value and its OA-catchment median, was 0.061 AMAI points for cycling, with an approximate 95% confidence interval of 0.048 to 0.075; in practical terms, this means that the typical OA-derived estimate for a given MSOA differs from the actual MSOA value by about six hundredths of an AMAI point. Parity agreement, defined as the share of MSOAs for which the actual MSOA value and the OA-catchment median fall on the same side of the parity threshold of 1.0, was 93.0% ($p < 0.001$). The share of actual MSOA values lying inside the OA-catchment p10-p90 interval, that is, between the 10th and 90th percentiles of OA values inside the same catchment, was 73.9%; this was below the nominal 80% benchmark implied by that interval, but only weakly so ($p = 0.075$). For overall walking AMAI, the equivalent figures were Pearson $r = 0.574$ and Spearman $\rho = 0.636$ with both $p < 0.001$, MAE $= 0.049$ with a 95% confidence interval of 0.039 to 0.060, parity agreement 97.9% ($p < 0.001$), and p10-p90 coverage 73.2% ($p = 0.047$). The test comparing actual MSOA values with OA-catchment medians did not indicate a systematic offset for either mode (walking $p = 0.386$, cycling $p = 0.827$), which suggests that the main issue is local spread rather than consistent over- or under-estimation. OA heterogeneity within MSOA catchments nevertheless remained non-trivial: the median within-MSOA OA interquartile range, or IQR, which measures the spread of the middle 50% of OA values inside each catchment, was 0.071 for walking and 0.080 for cycling. Figure 3 shows this relationship directly: MSOA values broadly track OA-catchment medians, but meaningful neighbourhood-scale variation remains, so MSOA geography captures strategic spatial structure while OA geography retains additional local detail.

4.3 Spatial Clustering at OA Level

OA-level AMAI values are not randomly distributed in space. For overall walking AMAI, Moran’s I is 0.484 ($p = 0.002$), while for cycling it is 0.476 ($p = 0.002$). High-high clusters account for 10.7% of OA origins for walking and 10.8% for cycling, while low-low clusters account for 7.3% and 6.7% respectively. This indicates that high and low competitiveness tend to form geographically coherent areas rather than isolated points, which strengthens the use of AMAI for spatial targeting and area-based intervention planning. Figure 4 shows the local clustering pattern for overall walking and cycling AMAI at OA level. Because these clusters are spatially contiguous, they can be treated as intervention units rather than as disconnected high- or low-scoring points. In particular, high-high clusters may identify self-reinforcing local environments where improvements to safety, continuity, or public realm quality could consolidate and extend already favourable conditions for active travel.

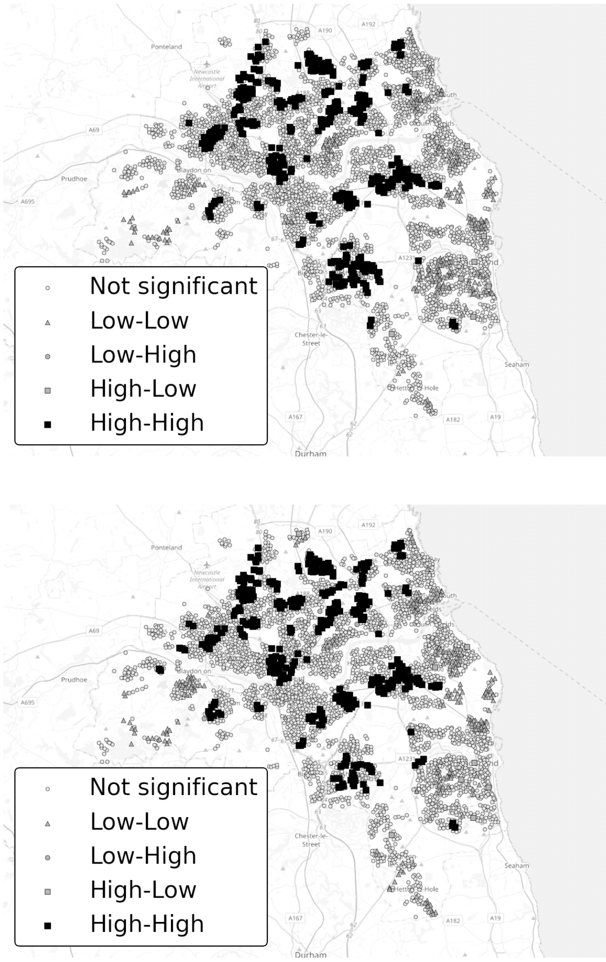

Figure 4. Local spatial clustering of OA-level AMAI. The top panel shows walking and the bottom panel cycling. High-high and low-low clusters indicate contiguous areas of relatively strong and relatively weak active travel competitiveness across the urban study area. Map data: OpenStreetMap contributors

4.4 Focus Area Illustration: Newcastle upon Tyne

Newcastle upon Tyne was selected for more detailed analysis because it is the strongest-performing local authority in the Tyne and Wear results and therefore provides a clear case for illustrating AMAI as a planning and diagnostic tool. Across 968 origins, Newcastle records the highest median cycling AMAI at 0.845 and the highest median walking AMAI at 0.662, with parity shares of 12.2% for cycling and 1.9% for walking. These values indicate that, although parity remains limited overall, Newcastle contains a stronger base of local active-travel competitiveness than the other authorities in the study area. The Newcastle cycling cluster map in Figure 5 shows that this competitiveness is not evenly distributed but forms coherent neighbourhood-scale clusters of relatively strong cycling competitiveness, making the city a useful setting for identifying where latent potential already exists and where structural intervention is still needed.

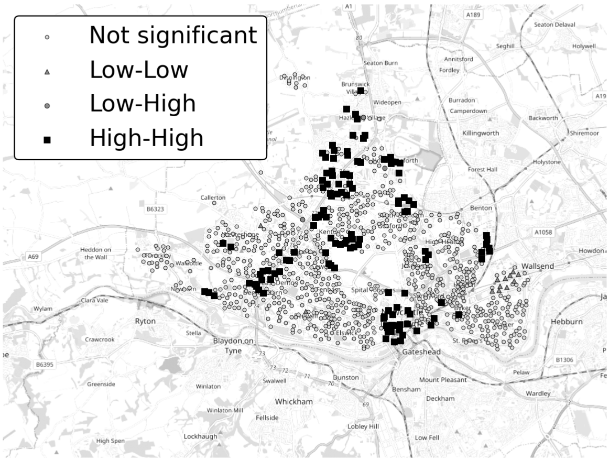

Figure 5. Local spatial clustering of OA-level cycling AMAI in Newcastle upon Tyne. High-high and low-low clusters indicate contiguous areas of relatively strong and relatively weak cycling competitiveness, showing that cycling performance is spatially concentrated rather than randomly distributed across the city. Map data: OpenStreetMap contributors

5. Validation

We compare AMAI with OA-level Census 2021 journey-to-work mode shares as supporting evidence that the index captures a behavioural signal. Because AMAI is intended primarily as a diagnostic of network competitiveness rather than a predictive model, the validation asks whether higher AMAI is associated with higher walking and cycling shares before and after controlling for commute-distance composition and terrain gradient.

The validation uses a common intersection sample of 3,864 OA-level records across the five Tyne and Wear local authorities: Newcastle, Gateshead, North Tyneside, South Tyneside, and Sunderland. Invalid AMAI rows coded as -1 were dropped, indicating cases where the routing workflow generated insufficient valid origin-destination information to compute a reliable AMAI value. Mode shares were computed over travellers rather than the full census denominator, i.e. excluding working from home. We compare four scenarios: raw (AMAI related to mode share without additional controls), distance-controlled, gradient-controlled, and jointly controlled for distance and gradient. The joint-control case is treated as the primary scenario. The importance of these feasibility constraints is illustrated in Figure 6: the top panel shows the negative relationship between walking share and approximate mean commute distance, while the bottom panel shows the negative relationship between cycling share and mean terrain gradient. At the pooled OA level, raw associations were positive for both walking and cycling, even though the feasibility constraints shown in Figure 6 account for a substantial part of observed variation in active mode share. For walking, Pearson $r = 0.167$ ($p = 1.277 \times 10^{-25}$) and Spearman $\rho = 0.154$ ($p = 5.612 \times 10^{-22}$). For cycling, Pearson $r = 0.152$ ($p = 2.769 \times 10^{-21}$) and Spearman $\rho = 0.150$

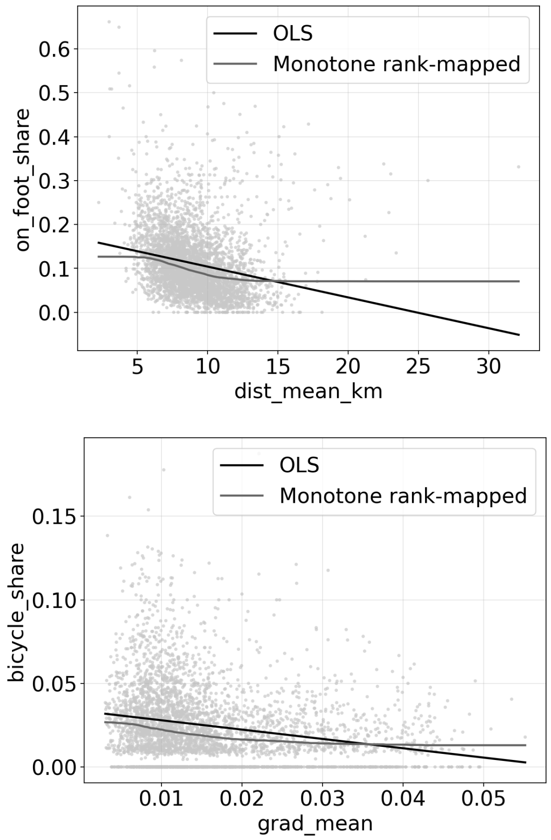

Figure 6. Major feasibility constraints in observed active travel across Tyne and Wear at OA level. The top panel shows the relationship between walking share and approximate mean commute distance, bottom panel shows the relationship between cycling share and mean terrain gradient. These variables are therefore included as controls in the validation analysis.

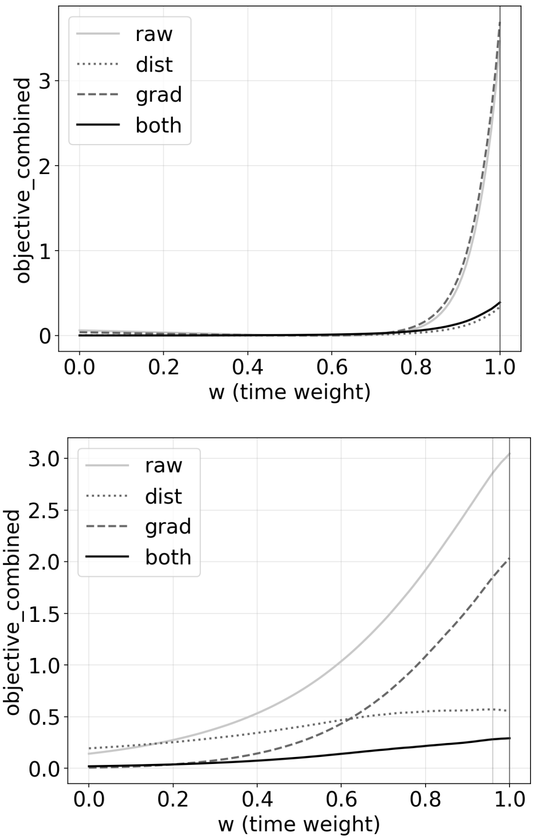

Figure 7. Validation-based calibration of the relative weight on time and distance components in AMAI across Tyne and Wear. The top panel shows walking and the bottom panel shows cycling under raw, distance -controlled, gradient-controlled, and jointly controlled scenarios. Validation favours a predominantly time-based specification, especially under joint control.

($p = 8.848 \times 10^{-21}$). Under the primary joint-control scenario, the associations attenuated but remained positive: for walking, Pearson $r = 0.102$ ($p = 1.933 \times 10^{-10}$) and Spearman $\rho = 0.066$ ($p = 4.532 \times 10^{-5}$); for cycling, Pearson $r = 0.083$ ($p = 2.898 \times 10^{-7}$) and Spearman $\rho = 0.061$ ($p = 1.661 \times 10^{-4}$). These results indicate that AMAI captures a modest but detectable behavioural signal beyond major feasibility constraints, while also confirming that commute-distance composition and terrain gradient are important correlates of observed mode share. For policy purposes, this means AMAI should be interpreted as one diagnostic component within a wider evidence base rather than as a direct predictor of uptake. We also examined the relative contribution of the time and distance components by scanning a weight parameter w in a convex combination of the two components during validation (Figure 7, top panel walking, bottom panel cycling). In the pooled regional sample, the time component consistently dominated this calibration exercise: the chosen weight on time was $w = 1.00$ for walking under all tested scenarios, and $w = 1.00$ for cycling under the raw, gradient-controlled, and jointly controlled scenarios, with $w = 0.96$ under distance-only control. We treat this result as supporting evidence about behavioural alignment in this dataset, not as a basis for redefining the main equal-weight AMAI specification used elsewhere in the paper. The calibration exercise therefore serves as a validation aid to interpretation rather than as a replacement for the policy-oriented default AMAI definition. Within individual local authorities, controlled associations were generally weaker and in some cases negative. This heterogeneity indicates that AMAI should be interpreted alongside local context and other determinants of active travel. The main implication is not that AMAI predicts uptake precisely, but that it can help identify where network competitiveness is or is not present, and where differences between structural potential and observed behaviour point to additional barriers or enabling conditions beyond network structure.

6. Discussion

Active Mobility Accessibility Index measures how competitive active modes are against car travel for short trips. The results it produces are consistent across spatial scales of the data, with finer-grained inputs resulting in more variability but the same hierarchy, distance effects, and modal patterns. The method can easily be applied in many spatial contexts. Logic of the score, combining time and distance parity, is an interpretable measure that can be verified by inspecting generated routes between origins and destinations. It is supported by transparent construction, by using medians across directions to reduce sensitivity to edge locations, and by validation evidence showing that the metric carries a modest but detectable association with observed walking and cycling shares. The value of AMAI is therefore primarily diagnostic and comparative rather than predictive, and lies in helping distinguish where local network conditions already support active travel and where structural deficits remain. AMAI is a direct measure of the competitiveness of the active travel network relative to driving. Madian values across analysed datasets is below 1.0 for both walking and cycling, which can be expected when cars, by design, move faster than these two modes. Temporal variations, stop-start movement patterns and indirectness of how road transport can be organised in urban areas do however make the active modes occasionally more performant, especially for short journeys. Uncertainty now arises less from opaque routing logic and more from the explicit assumptions of the in-house model, including the OpenStreetMap snapshot used, preprocessing choices, default speeds where attributes are missing, and the treatment of signal delay. Centroid-based representation of origins also introduces scale-dependent uncertainty: as zones grow, a score derived from a single point becomes less representative because it does not capture within-zone heterogeneity of network structure. This can be mitigated through multi-origin sampling (e.g. a grid) or by aggregating results and focusing on summary indicators. Initial API-based tests suggested that, for the short local trips studied here, time-of-day effects were limited relative to network structure and directness. This motivated use of a static in-house routing model for the main analysis. That simplification should not be read as a claim that congestion never matters, but rather that it was not a major differentiator for the short local trip lengths examined here.

From a policy perspective, AMAI is useful because it isolates the competitiveness of local network structure. High AMAI values indicate places where active modes already perform well enough that behaviour change, safety, or maintenance measures may be effective. Low AMAI values indicate structural disadvantage, especially where low distance parity points to severance or missing permeability and low time parity points to route friction, junction delay, or weak priority for active modes. Potential causes include missing crossings, long signal wait times, indirect street layouts, cul-de-sacs, river barriers, railway barriers, motorway severance, missing walking links, missing cycling links, discontinuous footways, discontinuous cycle tracks, one-way systems that favour fast driving, limited filtered permeability, high traffic speeds, high traffic volumes, complex junction geometry, poor bridge or tunnel provision, legal access restrictions or poor surface condition.

A parity threshold remains a useful interpretation benchmark, exposing the absolute competitiveness of travel by active modes. Equal weighting between time and distance is retained in the headline AMAI specification for interpretability and policy communication, while the validation results indicate that time parity aligns more strongly with observed mode shares in this dataset. Alternative weighting may therefore be useful in context-specific applications. The AMAI method is a scalable, policy-relevant indicator: it is indicative at MSOA level for strategy and revealing at OA for planning. MSOA aggregation smooths out micro-scale features, while OA-level sampling, captures structural details, allowing identification of clusters of highly performant network structures. A key policy message for the urban authorities is that where short-trip cycling is already competitive, targeted interventions that improve safety, comfort, and continuity may convert latent opportunity into everyday uptake. The OA-level clustering results show that high and low competitiveness are spatially concentrated, which means interventions can be targeted at coherent neighbourhood-scale areas rather than dispersed isolated locations. Walking remains below parity over much of the network but can reach high performance where block sizes are small and crossings are frequent, which points directly to the importance of permeability, crossing provision, and town-centre street design. At the same time, the weaker and sometimes negative within-LAD validation results under controlled specifications show that AMAI should be interpreted alongside terrain, trip-distance structure, road danger, perceived safety, personal security, public transport quality, age structure and workplace distribution rather than as a universal causal proxy for active travel uptake.

The same scoring framework can also be used in before-after assessment tools that test proposed network changes, such as filtering vehicular access on selected links or creating new walking and cycling connections, allowing accessibility gains to be assessed before implementation.

7. Conclusions

Active Mobility Accessibility Index offers a quantitative measure of how transport networks shape competitiveness of walking and cycling relative to driving. By integrating distance and time parity into a single score, AMAI covers both the geometric and temporal elements of accessibility, using equal weighting as a default diagnostic specification. Applied to region- and citywide settings, the index provides a consistent comparative framework across scales, while finer geographies reveal more local variation. Systematic sampling of origin-destination pairs and aggregation across distances and directions, provides stable and comparable representation of network's performance, from a mode-comparative perspective. The index measures structure, not safety, comfort or other qualitative factors that strongly mediate uptake. Method's outputs allow identification of areas with latent potential, where modal shift can be achieved with behaviour change, improved active travel infrastructure and traffic calming; and areas constrained by network's structure, where new paths and short-cuts are needed to minimise systemic discrimination of active travel users. Added value of AMAI is in locating latent competitiveness and attributes it to measurable network features. Practitioners can use AMAI as a diagnostic, benchmarking, and scenario-testing tool within a wider active travel toolbox. The observed OA-level clustering of both walking and cycling AMAI further suggests that the method is useful for identifying geographically coherent priority areas for intervention. Planners mapping areas parity can identify neighbourhoods where small improvements to connectivity would produce accessibility gains to otherwise disadvantaged communities. Similarly, existing networks in identified high opportunity areas can catalyse widespread mode shift upon improving perceptions of safety and convenience of local journeys. For broader benchmarking, the method can be applied across areas with contrasting morphologies to evaluate how urban layout affects network competitiveness profiles and to compare where investment is most likely to produce structural gains. Future work can evaluate how parity shifts under network edits and sampling protocols. Validation against OA-level Census 2021 mode shares, with controls for commute-distance composition and terrain gradient, shows that AMAI captures a modest but statistically detectable behavioural signal. This supports the practical relevance of the index, while leaving its main value in diagnosis and comparison rather than prediction. In summary, the introduced AMAI scoring method provides a clear, scalable and interpretable means of quantifying the competitiveness of walking and cycling relative to driving. Because the score can be recalculated under proposed network edits, AMAI is relevant for informing investment prioritisation and testing before-after intervention scenarios. AMAI frames accessibility as a comparative property of network structure, offering a practical foundation for diagnosis, benchmarking, and investment prioritisation in more efficient, attractive and equitable transport systems.

8. Data Availability

The main analysis used OpenStreetMap street-network data and routing graphs derived from those data. OpenStreetMap data are available under the Open Data Commons Open Database License (ODbL), and reused data or derived map products credits OpenStreetMap contributors (OpenStreetMap Foundation, 2026). Population-weighted Output Area (OA) and Middle Super Output Area (MSOA) points, together with Census 2021 journey-to-work mode-share and distance-to-work data, were obtained from the Office for National Statistics (ONS). ONS data are available under the Open Government Licence v3.0 (The National Archives, 2026). Terrain data were obtained from the Defra Data Services Platform; these data are also generally available under the Open Government Licence v3.0 (Department for Environment, Food & Rural Affairs, 2026, The National Archives, 2026).

An initial exploratory phase used the Google Maps Directions API to test whether time of day materially altered driving times for the short local trips considered here. No maps, route geometries, or results presented in this manuscript are reproduced from Google Maps Platform content beyond the statement that those initial tests suggested limited time-of-day effects for these trip lengths. Google Maps Platform services are subject to Google’s licence terms and attribution requirements (Google, 2026a, Google, 2026b).

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