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BIKE (Bicycle Integration Key Elements) Index: Benchmarking urban bikeability and cycling readiness. Evidences from European capitals

Alejandro Quintero Gómez, Pablo Calvo-Bascones [a],*

[a] Comillas Pontifical University - Institute for Research in Technology, Madrid, Spain

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ABSTRACT

This study introduces the BIKE Index, a multi-dimensional and reproducible framework for evaluating urban cycling conditions across cities, developed in response to the lack of standardized tools for assessing bikeability in urban areas. The index integrates four key dimensions into a composite score: Cycling Infrastructure, Cyclist Services, Environmental Constraints, and Safety and Street Quality. The dimensions are derived from open data sources, and consistent geospatial methods, including urban perimeters derived from Local Administrative Units and a standardized set of 210 cycling routes per city.

The methodology is applied to thirteen European capital cities using harmonized data from OpenStreetMap, OpenRouteService, Eurostat, Google maps, and E-OBS climate datasets. The results reveal significant disparities in cycling conditions, with scores ranging from Amsterdam (best) to Rome (worst). While infrastructure emerges as the primary differentiator, services, environmental factors, and safety also play critical roles. These findings suggest that creating cycling-friendly cities requires coordinated progress across all four dimensions. The BIKE Index offers a transparent and scalable methodology for benchmarking cycling conditions, enabling consistent comparisons and supporting evidence-based planning and policy making strategies.

1. Introduction

1.1. Urban cycling assessment in the context of European sustainability goals

European cities face unprecedented pressure to achieve a 90% reduction in transport emissions by 2050 as mandated by the European Green Deal (European Commission, 2025a). Transport currently accounts for approximately 25% of EU greenhouse gas emissions (European Environment Agency, 2023), with these figures continuing to rise despite overall emission reductions across other sectors. Against this backdrop, cycling has emerged as a cornerstone solution for sustainable urban mobility (European Commission, 2025b), offering a low-cost, low-carbon alternative that directly contributes to climate mitigation and public health objectives. The dual benefit of reducing emissions while enhancing health has been underscored in recent studies focusing on bicycling infrastructure's role in mitigating chronic diseases and improving population well-being (Wali, Frank, Chapman, & Fox, 2024).

The momentum behind cycling as a sustainable transport solution is undeniable across European cities. Recent data confirms remarkable growth patterns: cycling to work in the Netherlands increased by 57% between 2024 and 2025 (EU Urban Mobility Observatory, 2025), while Paris recorded a 166% surge in cycling traffic following strategic infrastructure investment (European Cyclists' Federation, 2025). This growth reflects broader European recognition that cycling contributes €150 billion annually to the European economy, with over €90 billion attributed to environmental, health, and mobility benefits (European Cyclists' Federation, 2018). Similarly, bike-sharing systems across European cities have experienced steady growth, with availability increasing by 4% from 2016 to 2023 (European Environment Agency, 2025), highlighting an enhanced intensity of bicycle usage.

However, significant implementation gaps persist across European cities. Daily cycling rates vary dramatically, ranging from 51% in Dutch cities to less than 1% in Greece and Portugal (Cycling Industry News, 2024; Monteiro, Sousa, Natividade-Jesus, & Coutinho-Rodrigues, 2023), revealing substantial disparities in how effectively cities support cycling infrastructure and culture. While cities investing in cycling infrastructure experience substantial increases in bicycle usage (Urban Land Institute, 2025), many urban areas continue to lack systematic assessment tools necessary to guide evidence-based policy decisions and benchmark progress. This gap is particularly notable when compared to evolving trends in smart urban transport policies, which

* Correspondence to: Department of Quantitative Methods, Comillas Pontifical University - Institute for Research in Technology, Rey Francisco 4, 28008 Madrid, Spain.
E-mail address: pcalvo@comillas.edu (P. Calvo-Bascones).

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have demonstrably shaped urban carbon emission trajectories in recent years (Lu, Xiao, Jiao, Du, & Huang, 2024).

1.2. State of the art

Urban cycling assessment has evolved significantly over the past two decades, with various frameworks emerging to evaluate bicycle-friendliness across cities, ranging from expert-based evaluations to quantitative network analyses using geospatial data.

1.2.1. Established global indices

The Copenhagenize Index represents the most influential global ranking system, evaluating cities based on fourteen parameters including bicycle infrastructure, facilities, traffic calming, modal share, safety, and political commitment (Copenhagenize Design Co., 2025). While widely cited as a benchmark, it relies on expert judgement with limited transparency, is not based on open and publicly accessible datasets. The PeopleForBikes City Ratings introduced data-driven quantitative analysis focusing on ridership, safety, network quality, and equity (PeopleForBikes, 2025). Clean Cities Campaign, publishes an European city ranking assessing bikeability as the extent of protected cycling infrastructure (Clean Cities Campaign, 2025). The Global Bicycle Cities Index by Luko evaluated 90 cities across weather, usage rates, safety, and infrastructure (EU Urban Mobility Observatory, 2022), but lacked methodological documentation, excluded relevant geographical factors such as elevation and city morphology, and is now defunct following GetSafe's acquisition (Getsafe, 2025).

1.2.2. Related literature and research lines

Academic literature has established bikeability as central to cycling evaluation. Winters, Brauer, Setton, and Teschke (2013) developed a foundational bikeability index based on facility availability, connectivity, topography, and land use, producing high-resolution spatial maps. Hardinghaus, Nieland, Lehne, and Weschke (2021) expanded this through multifactorial indices weighted by expert surveys, while Weikl and Mayer (Weikl & Mayer, 2023) distinguished between local, route-wide, and network-wide indicators based on European design standards. Other studies employed Bicycle Level of Service (BLOS) for segment-level evaluation (Griswold, Yu, Filingeri, Grembek, & Walker, 2018) and behavioural modelling approaches. Studies like (Kellstedt, Spengler, Foster, Lee, & Maddock, 2021) provided a comprehensive review highlighting methodological diversity and the need for globally transferable, open-data-based tools. Or (Eren & Uz, 2020), which identifies four main aspects of cycling viability such as: cycling Infrastructure, cyclist Services, environmental constraints, and safety & street quality.

Parallel studies have measured bikeability in terms of network performance low-stress connectivity (Furth, Mekuria, & Nixon, 2016), detour-based accessibility (Chou, Paulsen, Nielsen, & Jensen, 2023), topological structure readiness (Herrera-Acevedo & Sierra-Porta, 2025), or bicycle network quality (Argyros, Jensen, Rich, & Dalyot, 2024) — based on data sources ranging from open routing services to dockless trajectory records (Wang et al., 2024; Xu et al., 2019; Zhang, Shen, & Zhao, 2021). The environmental and operational context has gained prominence across complementary fronts. Exogenous conditions, terrain and broader urban form, shape shared e-bike utilization (Li, Qin, & Xu, 2025), while climate, particularly extreme temperatures, constrains operational resilience (Zheng, Liang, Wang, & Ou, 2025). The provision of services is increasingly guided by equity and intermodal objectives through bike-share station siting (Fan & Harper, 2024a). Demand for cycling reflects socio-demographic determinants measurable in census-based models (Parkin, Wardman, & Page, 2008) and is mediated by modal-shift interactions between private car use and public transport (Yao, Zhang, & Li, 2025). System performance depends on design and operations, with optimization approaches informing network sizing and rebalancing (Soriguera & Jiménez-Meroño, 2020). Together, these strands support an integrated view in which environmental constraints, service design, travel behaviour, and operational management jointly govern urban bikeability.

Despite this progress, existing frameworks exhibit significant limitations: focus on single dimensions without comprehensive integration, lack of systematic environmental constraint evaluation, spatial/temporal constraints limiting cross-city comparability, and dependence on subjective data that limits replicability. Addressing these gaps requires a holistic, reproducible, and multi-dimensional approach that leverages open data to capture real cycling conditions across diverse urban contexts. This study presents the BIKE (Bicycle Integration Key Elements) Index, which responds directly to this need, offering an integrated methodology designed to overcome the shortcomings of previous frameworks and enable consistent, evidence-based evaluation of cycling conditions. A comparative assessment of existing frameworks is presented in the Discussion (see Section 4), in Table 4.

1.3. Research contribution and objectives

In response to the research lines identified in the preceding section, the BIKE Index provides a standardized and transparent framework for evaluating urban cycling conditions across European cities. In contrast to existing approaches that either focus on isolated dimensions or depend heavily on subjective assessments, this research introduces a comprehensive methodology that integrates infrastructure quality, service accessibility, environmental constraints, and safety conditions through the systematic analysis of cycling routes. This aligns with recent findings emphasizing that multi-dimensional, data-driven assessments are essential for designing effective and equitable cycling policies (Wali et al., 2024) as well as identifying aspects that demonstrably increase bicycle use (Hajilari, Habibian, Moeinaddini, & Davoodi, 2025).

Developed entirely on open data sources, one of the main contributions of this work is that it does not rely on survey-based or national/local datasets, which typically limit cross-country comparability. By building exclusively on reproducible and accessible data, the BIKE Index ensures that results are directly comparable across cities with heterogeneous institutional contexts and data collection practices. The framework applies a route-based assessment rather than static network analysis, thereby capturing real conditions along recommended cycling paths. It also integrates environmental factors, such as topography and climate, that are often overlooked in traditional indices, while employing standardized normalization procedures to ensure comparability between cities regardless of size, morphology, or baseline cycling conditions.

The research is structured around five specific objectives:

1. Design and validate a standardized methodology for assessing urban bikeability through a holistic composite index.
2. Develop a transparent, open-data framework for reproducible worldwide analysis.
3. Demonstrate policy relevance by applying the index to multiple European cities, highlighting its ability to enable robust cross-country comparisons.
4. Produce comparative results with clear visualizations that support evidence-based decision-making, including within-city diagnostics across the index's dimensions.
5. Benchmark the BIKE Index against external indicators and observed bicycle-usage statistics.

The methodology was applied and validated across thirteen European capital cities selected for their diversity in geography, size, and cycling maturity.

2. Methodology

The BIKE Index quantifies urban cycling integration and bikeability via a composite indicator that balances four complementary dimensions

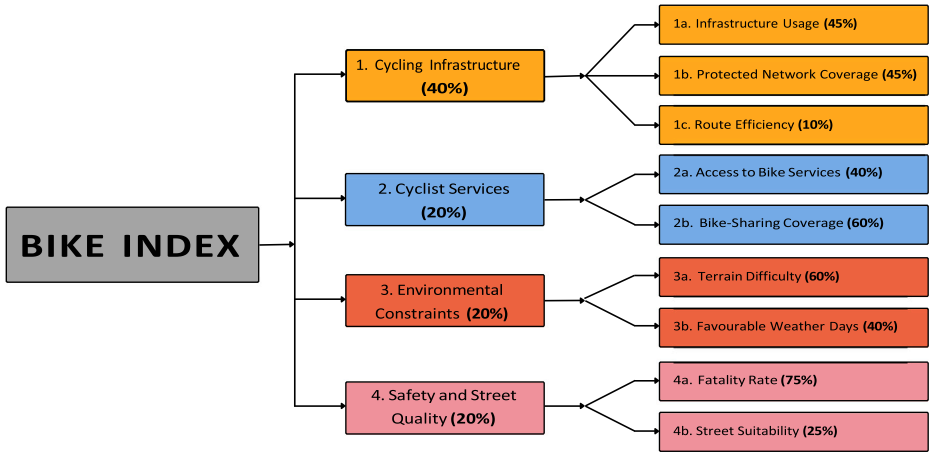

Fig. 1. Hierarchical structure of the BIKE Index, showing the four dimensions and their corresponding variables.

frequently discussed in the literature (Eren & Uz, 2020), each reflecting a distinct aspect of cycling viability:

1. Cycling Infrastructure
2. Cyclist Services
3. Environmental Constraints
4. Safety & Street Quality

Consistent with these determinants, the dimensionalization adopted in this study (Infrastructure, Services, Environment, Safety) aligns with established evidence: in addition to cycling infrastructure and services, climate conditions systematically influence usage and adoption of cycling mobility (Zheng et al., 2025). Terrain topography operates as a structural facilitator or barrier; hilliness reduces cycling propensity and shapes route choice through sensitivity to slope and distance (Li et al., 2025). Urban layout and network geometry condition effective accessibility via route directness; large-scale analyses using detour ratios show how network constraints impose circuitous travel and hinder cycling accessibility (Chou et al., 2023). Dimensions and variables were selected to reflect (i) proximity to the construct of bicycle-adoption, (ii) actionable levers within the cycling system—encompassing municipal policy authority and private-sector initiatives, and (iii) data coherence for cross-city comparability.

Spatially explicit aspects (e.g., facility type, infrastructures, cyclist services, etc.) require a sampling grid to map location and proximity. Grid resolutions commonly range from 100 to 500 m (Li et al., 2025; Xu et al., 2019; Zhang et al., 2021); coarser scales (> 500 m) may induce information loss due to excessive aggregation, although the optimal resolution remains study dependent (Wang, Zhan, Mi, Sobhani, & Zhou, 2022). Together, these strands of evidence situate the BIKE Index within ongoing methodological debates and justify its multidimensional design as a synthesis of the key determinants discussed in the literature.

Fig. 1 displays the dimensions and their associated variables, along with their weights, in a hierarchical diagram.

Weights are assigned in proportion to actionable leverage—dimensions that can be most directly improved through municipal policy or, where relevant, private initiatives are weighted higher, whereas largely exogenous, contextual, or subjective factors are weighted lower. In this study, the recommended BIKE Index weights are Infrastructure = 0.40 and Services = Environment = Safety = 0.20 each. Infrastructure receives the highest weight because it represents the greatest policy leverage at municipal scale and is directly modifiable through planning, capital investment, and standards-based design (e.g., expansion of protected facilities, intersection treatments, and improvements to network continuity). Services are important enablers but frequently reflect market-driven and socioeconomic conditions, with the notable case of public/private bike-sharing systems; a balanced weight avoids overstating factors not solely under municipal control. Environmental factors exert a critical but exogenous influence and are therefore weighted as contextual. Safety reflects the jurisdictional baseline set mainly by national policies (speed/legal frameworks, vehicle standards, enforcement, etc.). Street-suitability (quality) indicators tied to traffic conditions and user assessments are acknowledged within this dimension but are not overall overweighted to prevent double counting with infrastructure design.

An assessment of how alternative weighting schemes affect BIKE Index scores is presented in Section 3.4.

All analyses use open data sources and documented workflows to facilitate reproducibility. Central to the approach is a standardized network of 210 simulated cycling routes per city, generated with the OpenRouteService API and evaluated within a uniform 500 × 500 m grid. This schema captures both route-based attributes and proximity metrics without reliance on proprietary data.

2.1. Methodological framework

Before presenting the individual variables that compose the BIKE Index, it is essential to explain the common methodological foundations that apply to all cities and across all dimensions of the analysis.

2.1.1. Datasets

The BIKE Index relies exclusively on open or publicly available datasets to ensure full reproducibility and transparency. Table 1 summarizes all data sources used in the study, including their origin, year or version, estimation status, and functional role within the framework.

2.1.2. Urban area delimitation

Accurate definition of each city's study area is essential to ensure consistent spatial extent and avoid bias from non-urban land. The analysis begins with Local Administrative Unit (LAU) boundaries from Copernicus Urban Atlas, which provide pan-European coverage and alignment with municipal governance (Copernicus, 2022). However, since administrative perimeters often include uninhabited zones such as parks or industrial areas, we refined them using population density data from the Global Human Settlement Layer (GHSL). Only areas exceeding $1000\ \mathrm{inhabitants/km^2}$ were retained, following established thresholds for defining urban cores in European studies (Freire, Macmanus, Pesaresi, Doxsey-Whitfield, & Mills, 2016; Pesaresi et al., 2024).

The resulting high-density clusters were clipped to the LAU outline and merged into a single polygon representing the inhabited urban core. To remove narrow extensions and small fragments that could distort routing, a morphological smoothing operation was applied: a 1500 m negative buffer followed by a positive buffer of the same size,

Table 1
Overview of datasets used in the BIKE Index.

Dataset / Source	Year / Version	Estimation Status	Role in BIKE Index
OpenStreetMap (OSM)	2025	*Crowd-sourced — updated by volunteers*	Base map for street network
OpenRouteService (ORS) API	2025	*Modeled — computed from OSM data.*	Simulates 210 cycling routes per city and provides segment metadata
Copernicus Urban Atlas / Local Administrative Units (LAU)	2022	*Official — published by the European Commission*	Defines initial city boundaries for perimeter generation
Copernicus Global Human Settlement Layer (GHSL)	2020	*Official — published by the European Commission*	Used to identify dense areas and generate the "refined perimeter"
E-OBS Climate Dataset (v31.0e)	2015–2025	*Official — published by the European Commission*	Provides daily temperature and precipitation data for indicator 3b
Google Maps (Places API / web scraping)	2025	*Proprietary, public data — provided by a private company based on user inputs*	Source for coordinates of bike shops and bike-sharing stations (indicators 2a and 2b)
ITF / WHO Discussion Paper: “Cycling Safety Roundtable”	2018	*Official — published by the OECD*	National cyclist fatality rates per million km cycled, used as city-level safety proxy (indicator 4a)
Report on the Quality of Life in European Cities	2023	*Official - published by the European Comission*	Provides data on bicycle usage rates, used for validation and comparison with external benchmarks

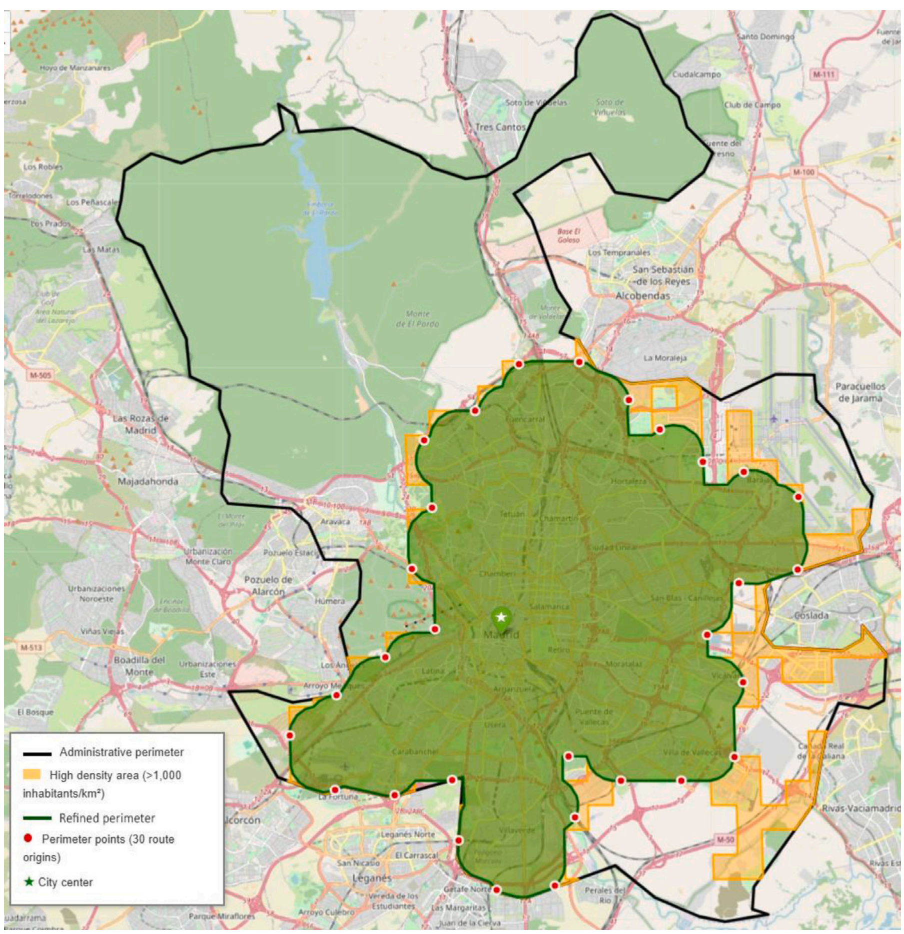

Fig. 2. Comparison between administrative, high-density, and refined urban perimeters for Madrid.

executed in EPSG:3857 to ensure metric accuracy. The final geometry was then reprojected to EPSG:4326 for consistency with the other spatial datasets used in this study. This re-projection step is necessary because the buffering operation requires a projected coordinate system with metre-based units, whereas the analytical and visualization layers use geographic coordinates.

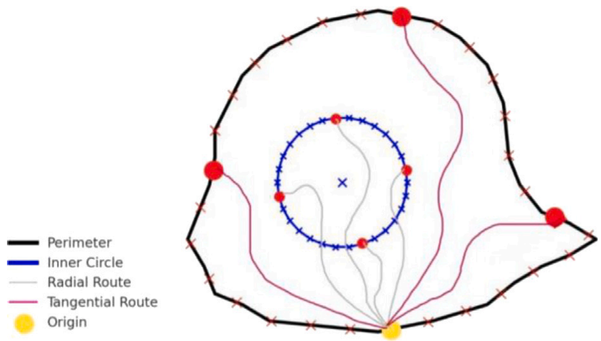

Fig. 3. Schematic representation of the seven routes generated from one of the 30 perimeter points. The same process is applied to all remaining points to produce the complete set of 210 routes.

Fig. 2 illustrates the procedure for Madrid, showing the original administrative boundary, the areas exceeding the 1000 $inhabitants/km^2$ density threshold, and the final refined and smoothed perimeter used as the study boundary. The figure highlights how relying solely on administrative limits would include extensive uninhabited zones such as parks and open land, distorting spatial indicators. Likewise, without the buffering and smoothing steps, the perimeter would retain irregular shapes and clustered points, introducing geometric artefacts that could bias routing and coverage analyses.

2.1.3. Route network generation

To analyse cycling infrastructure and accessibility in a spatially realistic and methodologically consistent way, this study simulates urban bicycle mobility through a standardized set of routes for each city. Each city's perimeter, calculated in Section 2.1.2, is sampled at 30 geodesically equidistant points. From each perimeter point, seven routes are generated, which follow two primary patterns of urban movement:

- **Radial mobility:** Four radial routes to an inner ring of 30 points, positioned at the same bearing and located at half the minimum perimeter-centre distance or 1.5 km, whichever is greater. These routes mimic typical commutes for work, education, or services.
- **Tangential mobility:** Three tangential routes to other perimeter points at 90°, 180°, and 270° offsets, which capture circumferential flows across districts.

Fig. 3 illustrates, as an example, the 7 connections (4 radial and 3 tangential) originating from a single perimeter point. This example represents the process that will be applied to each of the 30 points along the perimeter.

This final result yields 210 routes per city, balancing spatial representativeness with computational tractability and reflecting both inbound and circumferential travel patterns observed in urban cycling behaviour (Boyce, 2006; Zhao, Yuan, & Zhang, 2022).

This design ensures uniform directional and morphological coverage and captures the two dominant macroscopic movement archetypes—inbound and circumferential—that collectively assess continuity, surface type, steepness gradient, and traffic segregation. Although origins are peripheral, computed paths systematically traverse the urban core: converging radials and their intersections with tangentials repeatedly sample central links as subpaths, yielding high "edge exposure" for short intra-core trips. As BIKE Index targets infrastructure readiness rather than the empirical distribution of trip lengths, a minimum probe length is enforced so each trajectory spans multiple junctions and contexts. Sampling beyond 210 routes adds mostly redundant trajectories with limited gains in unique link exposure while materially increasing computational cost; the 210-route scheme thus balances representativeness and tractability across heterogeneous urban layouts.

Routing employs ORS's "cycling-regular" profile to prioritize safety and infrastructure continuity; the API returns detailed segment-level metadata (waytype, steepness, surface, suitability) (OpenRouteService, 2024b) used to compute multiple variables.

Fig. 4 shows the complete set of 210 generated routes for Berlin.

2.1.4. Analytical grid

Proximity-based variables are calculated on a 500 m square grid. The 500 m tile size reflects a 5–7 min walking distance widely cited in urban accessibility literature (Frank, Schmid, Sallis, & Chapman, 2005; Gehl, 2011). This grid underpins all spatial coverage metrics, ensuring uniform granularity across cities of varying size and morphology.

2.2. Dimension 1: Cycling infrastructure

This dimension quantifies the physical foundation for cycling mobility through three complementary metrics that capture infrastructure presence, spatial accessibility, and functional performance. Infrastructure receives the highest weighting (40%) based on empirical evidence demonstrating its role as the primary determinant of cycling uptake, with bikeability coefficients reaching 75% of the total weight in some predictive models (Ahmed, Pirdavani, Wets, & Janssens, 2025; Schoner & Levinson, 2014).

Within this dimension, weights are allocated as follows: Infrastructure Usage (45%), Protected Network Coverage (45%), and Route Efficiency (10%), prioritizing observed utilization and protection while preserving sensitivity to network directness.

2.2.1. Variable 1a: Infrastructure usage

This variable evaluates cyclist-friendly infrastructure quality along the 210 routes simulated in Section 2.1.3, measuring practical accessibility rather than mere existence. Routes are decomposed into segments classified by ORS waytype metadata (OpenStreetMap Wiki, 2025) with weights reflecting cycling suitability: dedicated lanes (1.0), paths or tracks (0.8), shared footways (0.5), and other segments (0.0).

The infrastructure score is calculated as shown in Eq. (1).

$$I = \frac{\sum_{j=1}^{n} \frac{\sum_i d_{i,j} w_{i,j}}{L_{total,j}}}{n} \times 100 \tag{1}$$

where I is the infrastructure usage index (%), $d_{i,j}$ is segment length (m), and $w_{i,j}$ is suitability weight of segment i of route j, $L_{total,j}$ is the total length (m) of route j, and n is the total number of routes.

This approach recognizes that infrastructure must be continuous and safe to support everyday cycling, particularly for cautious users (Gehl, 2011; Mulvaney et al., 2015).

For this variable, Amsterdam and Stockholm lead with scores of 74% and 72% respectively, while Athens ranks lowest at 7%, with over 85% of routes traversing regular streets without cycling roads.

2.2.2. Variable 1b: Protected network coverage

This spatial metric evaluates how extensively dedicated cycling infrastructure (OSM cycleway tags (OpenStreetMap Wiki, 2025)) reaches across the urban territory. All protected segments within the perimeter calculated in Section 2.1.2 are overlaid onto the 500 m grid from Section 2.1.4, with coverage calculated as shown in Eq. (2):

$$C = \frac{n_{\text{covered}}}{n_{\text{total}}} \times 100 \tag{2}$$

where C is the protected network coverage (%), n_{covered} is the number of grid tiles intersecting protected infrastructure, and n_{total} is the total number of tiles within the urban area.

Tiles intersecting any dedicated infrastructure are marked as covered. This approach prioritizes segregated infrastructure that demonstrably improves perceived and actual cyclist safety (Pucher & Buehler, 2016).

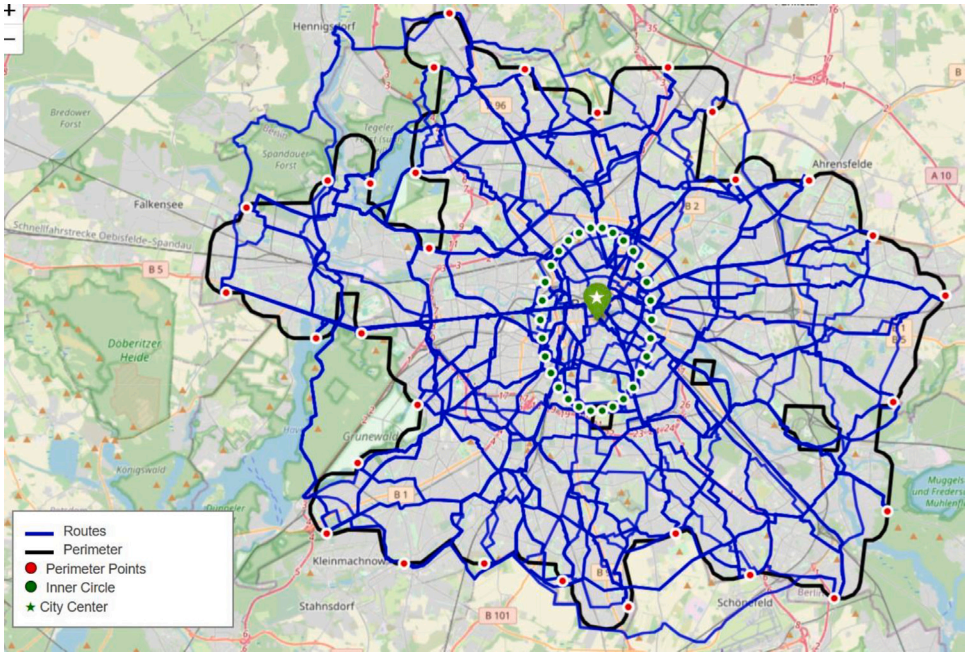

Fig. 4. Full set of 210 generated cycling routes in Berlin, combining perimeter–perimeter and perimeter–centre connections.

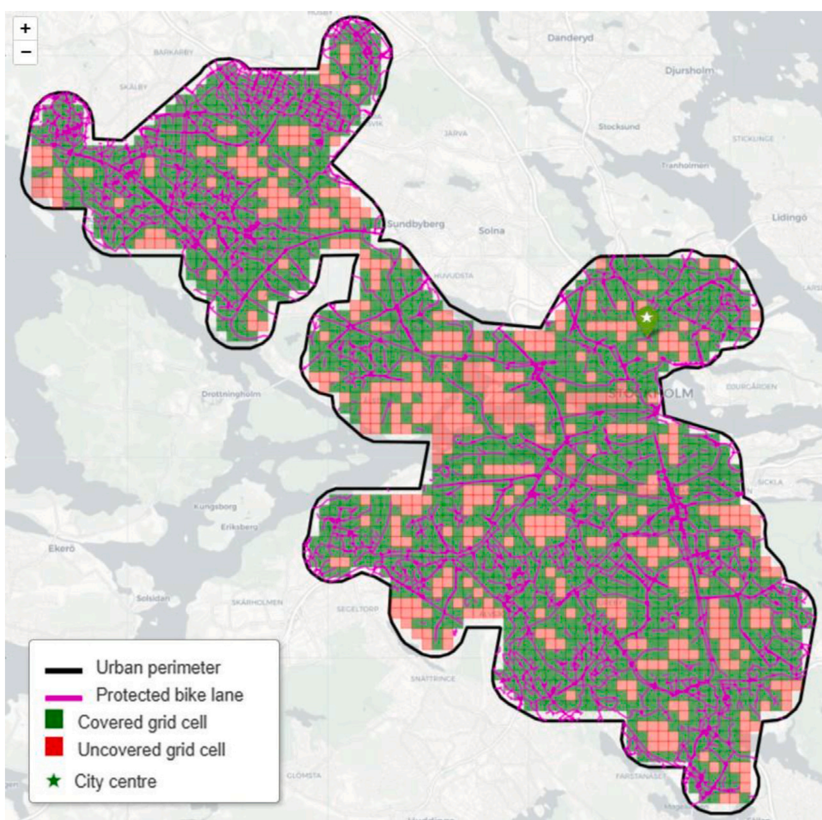

Fig. 5. Results of variable 1b: *Protected Network Coverage* for Stockholm.

Amsterdam leads with 81.8% grid coverage, followed by Stockholm (78.7%) and Paris (70.0%). Fig. 5 shows the Protected Network Coverage results for Stockholm.

Berlin presents an outlier case: despite over 1000 km of infrastructure, it achieves only 29.4% coverage. This reflects the city's unusually large administrative area and spatially concentrated network: most cycleways are located in central districts, leaving peripheral areas sparsely covered.

2.2.3. Variable 1c: Route efficiency

This metric assesses network geometric efficiency by comparing straight-line to actual route distances across all 210 routes simulated in Section 2.1.3, as shown in Eq. (3):

$$E = \frac{\sum_{j=1}^{n} \frac{d_{\text{straight,j}}}{d_{\text{real,j}}}}{n} \tag{3}$$

where E is the route efficiency index, $d_{\text{straight,j}}$ is the straight-line distance between origin and destination (m) of route j, and $d_{\text{real,j}}$ is the actual travelled distance (m) of route j, and n is the total number of routes (210).

Values approaching 1.0 indicate a street and path layout that allows near-direct travel between origins and destinations. Low values indicate substantial detours, which can arise from two distinct mechanisms: a complex urban topology that forces indirect routing for any mode, or a misalignment between bicycle-suitable corridors and the shortest desire lines that pushes cyclists onto longer but safer or legally permitted streets. Accordingly, this metric reflects properties emerging from both urban form and the configuration of cycle-appropriate links rather than being fully independent of infrastructure type. The lower weighting (10%) recognizes that, in practice, cyclists often trade some shorter routes for safer and more comfortable ones.

Athens achieves the highest efficiency 0.68, followed by Lisbon. Luxembourg and Stockholm score below 0.52.

2.3. Dimension 2: Cyclist services

This dimension evaluates the supporting ecosystem enabling practical bicycle use beyond dedicated infrastructure. Services receive equal weighting (20%) with environmental and safety dimensions, reflecting growing recognition that cycling promotion requires comprehensive support systems (Kwigizile, Oh, & Lyimo, 2019). The dimension captures both maintenance infrastructure for bicycle ownership and flexible access options through bike-sharing services.

Within the Cyclist Services dimension, weights are allocated as follows: Access to Bike Services (40%) and Bike-Sharing Coverage (60%), prioritizing the spatial reach of shared systems while retaining sensitivity to ancillary service availability.

2.3.1. Variable 2a: Access to bike services

This proximity-based variable quantifies spatial accessibility to bicycle repair shops and retail services across the urban grid calculated in Section 2.1.4. Cyclist services (e.g., repair shops, retail, secure parking, and bike-share stations) are sourced from the Google Maps Points of Interest (POI) directory due to its wide geographic coverage and frequent updates via business-owner submissions, user contributions, and platform verification. To enhance reliability, records marked as “permanently closed” were not included, categories were restricted to cycling-specific types, and duplicates were consolidated using normalized name–address keys. Each service point generates a 500 m buffer (representing walkable access distance), with grid coverage calculated as shown in Eq. (4):

$$A = \frac{n_{\text{covered}}}{n_{\text{total}}} \times 100 \tag{4}$$

where A is the access-to-bike-services index (%), n_{covered} is the number of grid tiles intersecting at least one service buffer, and n_{total} is the total number of grid tiles within the urban area.

Tiles intersecting any service buffer are marked as covered. This threshold aligns with established walkability standards and reflects the importance of maintenance infrastructure for bicycle ownership and use frequency (Krizek & Johnson, 2006).

Paris achieves the highest coverage (89.3%), while Copenhagen follows at 76.3%. Stockholm and Luxembourg show limited coverage (24.9% and 34.0%) with concentrated service clustering.

2.3.2. Variable 2b: Bike-sharing coverage

This variable measures public bike-sharing station accessibility using the exact same approach as Section 2.3.1, filtering service points for “bike sharing station” classifications. Station coverage receives higher weighting within the dimension based on evidence of bike-sharing’s significant impact on modal share and cycling culture development (Fishman, 2015; Shaheen, Guzman, & Zhang, 2010). Coverage is calculated identically to Section 2.3.1, following Eq. (5):

$$B = \frac{n_{\text{covered}}}{n_{\text{total}}} \times 100 \tag{5}$$

where B is the bike-sharing coverage index (%), n_{covered} is the number of grid tiles intersecting at least one station buffer, and n_{total} is the total number of grid tiles within the urban area.

This indicator is included as a service-availability metric that captures the spatial reach of public/shared bicycles and their potential to enable cycling for non-owners, occasional riders, tourists, and users facing temporary barriers to private bicycle use (e.g., repair, storage, or trip chaining). It also proxies integration opportunities with public transport through station siting (Fan & Harper, 2024b). In cities with mature cycling cultures and high private ownership, lower coverage values may coexist with high overall cycling activity; Accordingly, the indicator is not interpreted as a measure of “dependence” on third-party services but as an enabling infrastructure that supports inclusivity, resilience, and multimodal connectivity.

Paris achieves complete coverage (100%). Madrid and Copenhagen follow with high coverage (86.7% and 85.0%). Cities with established cycling cultures like Amsterdam and Stockholm show lower coverage (below 40% and 16.2% respectively).

Fig. 6 depicts the density and distribution of bike-sharing stations in Madrid.

2.4. Dimension 3: Environmental constraints

This dimension quantifies how natural environmental factors constrain cycling feasibility, focusing on immutable geographic and climatic conditions that cannot be easily modified through policy interventions. Unlike infrastructure-based metrics, these variables provide contextual baselines for interpreting cycling performance across different geographic settings. Environmental constraints receive equal weighting (20%) with services and safety dimensions, acknowledging their fundamental influence on cycling behaviour while recognizing their structural nature (Ahmed, Pirdavani, Wets, & Janssens, 2024; Valenzuela et al., 2022).

Within the Environment dimension, weights are allocated as Terrain Difficulty (60%) and Favourable Weather Days (40%).

2.4.1. Variable 3a: Terrain difficulty

This variable quantifies the physical effort imposed by topography along the 210 simulated cycling routes from Section 2.1.3, addressing the vertical dimension of cycling accessibility. Steep terrain reduces cycling uptake and affects route choice, particularly among less experienced users (Valenzuela et al., 2022). The methodology employs ORS steepness classifications, mapping each segment to effort weights: flat ±0%–1% (weight 0), mild ±1%–4% (weight 1), moderate ±4%–7% (weight 2), steep ±7%–10% (weight 3), very steep ±10%–16% (weight 4), and extreme $\pm > 16\%$ (weight 5). Slopes are considered in absolute terms, so negative gradients are treated as positive when computing effort, reflecting that any given route may be cycled in both directions. Terrain-difficulty values exceeding 1 were truncated at the upper bound of 1.

The slope-induced effort is calculated as a length-weighted average, as shown in Eq. (6):

$$T = \frac{\sum_{j=1}^{n} \min\left(\frac{\sum_i l_{i,j} w_{i,j}}{L_{\text{total,j}}}; 1\right)}{n} \tag{6}$$

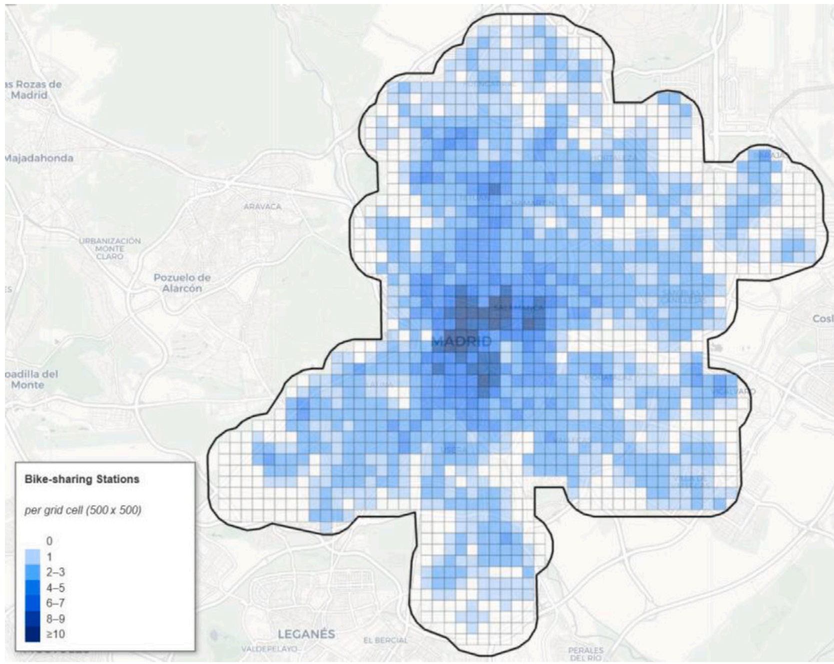

Fig. 6. Results of variable 2b: *Bike-Sharing Coverage* for Madrid.

where T is the terrain difficulty index, $l_{i,j}$ is the length (m) of segment i of route j; $w_{i,j}$ is the corresponding slope weight; and $L_{\text{total,j}}$ is the total length (m) of route j.

Since routes are unidirectional, absolute slope values capture bidirectional cycling challenges.

Higher weighting (60%) reflects terrain's immutable nature compared to climate, which can be partially mitigated through infrastructure adaptations. The values of this variable are inverted (lower-is-better scale) during the normalization process.

Amsterdam, Copenhagen, and Berlin exhibit near-zero scores with over 97% of segments in the flat category. Conversely, Luxembourg, Athens, and Lisbon score 0.77–0.81, reflecting significant elevation challenges. Luxembourg particularly stands out with over 10% of routes featuring slopes above 7%.

2.4.2. Variable 3b: Favourable weather days

This variable estimates the annual proportion of climatically suitable cycling days based on temperature and precipitation thresholds derived from behavioural cycling literature (Kane & Kythreotis, 2024; Pazdan, 2020). A day is considered unfavourable if any (at least one) of the following conditions are met:

- Minimum temperature below 0 °C
- Maximum temperature above 35 °C
- Precipitation exceeding 2 mm.

Daily climate data spanning 2015–2024 were extracted from the E-OBS ensemble dataset at 0.1° resolution for each city centre (European Climate Assessment & Dataset (ECA&D), 2024). The variable is calculated as shown in Eq. (7):

$$F = 1 - \left(\frac{N_{\text{unfav}}}{N_{\text{total}}}\right) \quad (7)$$

where F is the proportion of favourable weather days, N_{unfav} is the number of days exceeding any unfavourable weather threshold, and N_{total} is the total number of days in the analysed period.

The lower weighting (40%) reflects climate's partial mitigation potential through covered infrastructure, maintenance protocols, and complementary services, unlike immutable topographic constraints.

Athens, Lisbon, and Rome lead with over 78% favourable days. Amsterdam, Stockholm, and Luxembourg score 56%–60%, constrained by frequent rainfall (119 days annually in Amsterdam) and cold periods (over 80 days below 0 °C in Stockholm). Fig. 7 shows the daily climate profile in 2022 for the most rainy city in our sample, Amsterdam.

2.5. Dimension 4: Safety and street suitability

This dimension evaluates cycling safety and street-level conditions that affect cyclist comfort and perceived risk, extending beyond infrastructure provision to capture the operational reality of urban cycling environments. Safety consistently ranks as the primary barrier to cycling adoption, making this dimension critical despite its equal weighting (20%) with services and environmental factors (Winters et al., 2012). The dimension combines objective risk measurement with subjective street quality assessment to provide comprehensive safety evaluation.

Within the Safety and Street Suitability dimension, weights are allocated as Fatality Rate (75%) and Street Suitability (25%). Under the composite scheme, Fatality Rate receives the highest weight of any indicator within a single dimension and is the third-most influential variable overall in the BIKE Index—after Infrastructure Usage and Protected Network Coverage.

2.5.1. Variable 4a: Fatality rate

This variable provides an objective measure of cycling risk through exposure-adjusted fatality rates, enabling meaningful safety comparisons across countries with different cycling volumes. Unlike raw death counts, exposure adjustment accounts for usage intensity, following OECD/ITF standards for international transport safety assessment (Castro, Kahlmeier, & Gotschi, 2018). The metric is defined as shown in Eq. (8):

$$R = \frac{D_{\text{year}}}{K_{\text{cyc}}} \times 100 \quad (8)$$

where R is the fatality rate (deaths per 100 million km cycled), D_{year} is the number of annual cyclist deaths, and K_{cyc} is the total million kilometres cycled per year.

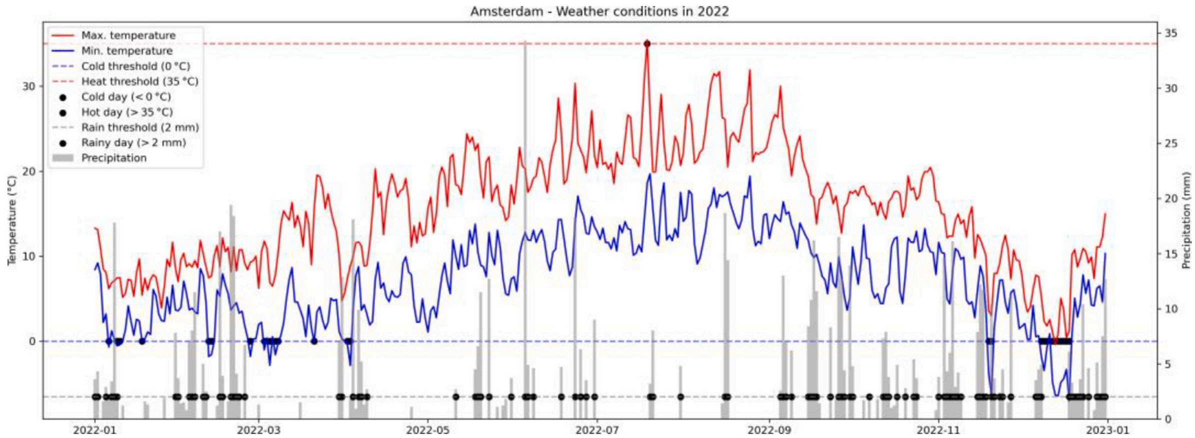

Fig. 7. Climatic Conditions in Amsterdam (2022) – Daily Temperature and Precipitation.

Data were extracted from Castro et al. (2018). National rates are assigned to capital cities as proxies, justified by strong correlations between national and urban safety trends despite the approximation this introduces.

This indicator is intended to provide an assessment at national/jurisdictional level (e.g., legal speed frameworks, enforcement regimes, and vehicle safety requirements) using harmonized national fatality statistics as standardized proxies. These proxies are interpreted as the baseline safety context to which all cities within a jurisdiction are subject. This study does not test a statistical relationship between infrastructure and fatalities; rather, the dimension is theoretically expected to align with lower risk in otherwise comparable settings.

The variable receives higher weighting (75%) as it provides empirical evidence of actual risk rather than inferred conditions. The values of this variable are inverted (lower-is-better scale) during the normalization process.

Results span from 0.2 deaths per 100 million km in Luxembourg to 5.1 in Italy, a 25-fold safety difference. The Netherlands achieves 0.8 despite extremely high exposure (over 15 billion km annually), demonstrating that infrastructure and policy can maintain safety at scale. It is important to clarify that all variables are subsequently normalized and adjusted to a 0–100 scale, as explained in Section 2.6, so that values remain comparable across cities.

2.5.2. *Variable 4b: Street suitability*

This variable assesses the overall quality of streets actually used by cyclists, capturing nuanced infrastructure conditions beyond binary presence/absence classifications. The methodology employs ORS suitability scores (0–1 scale) that integrate road classification, legal access, surface quality, and traffic characteristics based on OpenStreetMap data (OpenRouteService, 2024a). Scores reflect how well segments match cycling profile requirements, favouring segregated, calm, or legally accessible routes.

Street suitability is calculated as a length-weighted mean across all 210 routes from Section 2.1.3, as shown in Eq. (9):

$$S = \frac{\sum_{j=1}^{n} \frac{\sum_i s_{i,j} d_{i,j}}{L_{total,j}}}{n} \tag{9}$$

where S is the average street suitability index, $s_{i,j}$ is the ORS suitability score of segment i (0–1); $d_{i,j}$ is the length (m) of segment i of route j; $L_{total,j}$ is the total length of rout j; and n is the total number of routes.

The lower weighting (25%) reflects its nature as inferred rather than directly observed safety outcomes, though it provides valuable complementary perspective on street-level cycling conditions (Fuest et al., 2023).

Copenhagen leads with 0.91, followed by Brussels, Paris, and Stockholm (all > 0.89), where over 75% of route segments score above 0.9. Lower-scoring cities (Athens, Madrid, Rome, Lisbon) exhibit more fragmented networks.

2.6. *Normalization of individual variables*

Normalization is essential to integrate heterogeneous measures into a single composite score without allowing any one variable to disproportionately bias results. The BIKE Index employs a Modified Z-Score with Median Absolute Deviation (MAD), a method recommended by OECD guidelines for composite variables under non-normal distributions or extreme outliers (OECD, European Union, European Commission Joint Research Centre, 2008).

2.6.1. *Need for robust normalization*

Variables within the BIKE Index span percentages, continuous ratios and rates per exposure. Traditional min–max scaling would compress non-extreme cities into narrow bands when confronted with extreme values, obscuring meaningful differentiation (Ahmed et al., 2025). Similarly, standard z-scores are sensitive to extreme values that can distort mean and standard deviation. For this reason, the BIKE Index adopts a Modified Z-Score based on the median and MAD, which is more robust to outliers and better suited to non-normal distributions.

2.6.2. *Modified Z-score with MAD*

Unlike the standard z-score, which depends on the mean and standard deviation and is easily distorted by outliers, the Modified Z-Score uses robust statistics (the median and the Median Absolute Deviation (MAD)) to ensure stability. The method proceeds in three steps:

Step 1. Compute median and MAD for each variable.

$$\mathrm{MAD}_j = \mathrm{median}\left(|x_{i,j} - \tilde{x}_j|\right) \tag{10}$$

where $x_{i,j}$ is the value of city i in variable j, $\tilde{x}_j$ is the sample median of variable j and MAD_j is the Median Absolute Deviation of variable j.

Step 2. Calculate the Modified Z-Score for each observation.

$$Z^*_{i,j} = 0.6745\,\frac{x_{i,j} - \tilde{x}_j}{\mathrm{MAD}_j} \tag{11}$$

where $Z^*_{i,j}$ is the modified z-score for city i in variable j, and the constant 0.6745 scales MAD to the standard deviation of a normal distribution (IBM, 2025).

Step 3. Rescale to a 0–100 range.

$$N_{i,j} = \left[\frac{Z^*_{i,j} + k}{2k}\right] \times 100 \tag{12}$$

Table 2
Descriptive statistics of the raw BIKE Index variables before normalization.

City	1. Infrastructure			2. Services		3. Environment		4. Safety	
	1a	1b	1c	2a	2b	3a	3b	4a	4b
Amsterdam	74 %	82 %	0.57	56 %	39 %	0.00	60 %	0.80	0.87
Paris	58 %	70 %	0.64	89 %	100 %	0.18	73 %	2.80	0.89
Copenhagen	30 %	55 %	0.58	76 %	85 %	0.01	62 %	0.90	0.91
Stockholm	72 %	79 %	0.49	25 %	16 %	0.31	61 %	1.20	0.89
Vienna	65 %	54 %	0.61	44 %	57 %	0.24	69 %	2.40	0.89
Madrid	35 %	37 %	0.64	43 %	87 %	0.57	69 %	0.40	0.82
Brussels	38 %	51 %	0.63	54 %	84 %	0.35	62 %	2.40	0.90
Lisbon	40 %	53 %	0.64	55 %	24 %	0.78	83 %	1.00	0.78
Berlin	26 %	29 %	0.58	34 %	79 %	0.03	66 %	1.10	0.86
Luxembourg	38 %	35 %	0.51	34 %	55 %	0.81	56 %	0.20	0.87
Dublin	28 %	19 %	0.56	40 %	17 %	0.11	72 %	1.80	0.87
Athens	7 %	7 %	0.68	50 %	1 %	0.77	84 %	0.50	0.84
Rome	25 %	21 %	0.59	45 %	0 %	0.32	78 %	5.10	0.80
Average	41 %	45 %	0.59	50 %	50 %	0.34	69 %	1.58	0.86
Median	38 %	51 %	0.59	45 %	55 %	0.31	69 %	1.10	0.87
Max	74 %	82 %	0.68	89 %	100 %	0.81	84 %	5.10	0.91
Min	7 %	7 %	0.49	25 %	0 %	0.00	56 %	0.20	0.78

Variable	Description
1a – Infrastructure Usage	*Share of route length running on cyclist-friendly infrastructure (% of total route length)*
1b – Protected Network Coverage	*Percentage of grid cells intersecting cycleways (% area covered)*
1c – Route Efficiency	*Ratio between straight-line and actual route distances (dimensionless, closer to 1 = indicate direct routing)*
2a – Access to Bike Services	*Percentage of grid cells containing a bicycle oriented service (% area covered)*
2b – Bike-Sharing Coverage	*Percentage of grid cells containing a public bike-sharing station (% area covered)*
3a – Terrain Difficulty	*Length-weighted average of route steepness (index 0–1, where lower values indicate flatter terrain)*
3b – Favourable Weather Days	*Proportion of annual days suitable for biking (% of total days)*
4a – Fatality Rate	*Number of cyclist deaths per 100 million km cycled*
4b – Street Suitability	*Average suitability score (0–1) from OpenStreetMaps*

where $N_{i,j}$ is the normalized score (0–100 scale) of city i in variable j, and $k = 3$ defines the truncation threshold at ±3 standard deviation equivalents (Calvo-Bascones, Sanz-Bobi, & Welte, 2021).

Values outside this range are truncated to 0 or 100, ensuring all normalized scores remain within the interval.

Tables 2 and 3 report the descriptive statistics before and after normalization, respectively. During normalization, Terrain Difficulty and Fatality Rate are inverted to yield a lower-is-better scale. These tables illustrate the range compression achieved through the Modified Z-Score with MAD and confirm that all variables were subsequently rescaled to the 0–100 standardized domain shown in Table 3, which contains the final results of the BIKE Index.

2.6.3. Limitations

The Modified Z-Score with MAD presents some limitations: the standard choice of $k = 3$ (Calvo-Bascones et al., 2021) for bounding scores introduces an element of arbitrariness that affects how extreme values are compressed, though only one sample (out of 117) exceeded these bounds in our sample. Additionally, truncating scores at the 0–100 limits can understate the relative positions of exceptional performers. Despite these limitations, the Modified Z-Score with MAD delivers a transparent, reproducible, and theoretically sound basis for combining the BIKE Index's diverse variables into a single composite measure.

3. Results

The BIKE Index full results are shown in Table 3, and Fig. 8. The scores range from 60.5 (Amsterdam) to 34.2 (Rome), representing a 26.3-point spread in cycling conditions across the analysed European capitals. The composite results reveal distinct performance tiers: five cities achieve scores above 50, representing the most cycling-friendly environments; six cities cluster between 40–50 points, indicating moderate conditions; and two cities fall below 40, signalling significant cycling infrastructure and policy gaps.

3.1. Overall BIKE index performance

Amsterdam leads with the highest overall score (60.5), followed closely by Paris (59.6), and Copenhagen (55.2) as shown in Table 3, and Fig. 8. The upper-middle tier includes Stockholm (53.2) and Vienna (52.8). Madrid (49.0), Brussels (49.0), Lisbon (47.9) and Berlin (46.6) comprise the most average cities. The bottom tier comprises Luxembourg (44.4), Dublin (42.5), Athens (39.7), and Rome (34.2). These results demonstrate clear stratification in urban cycling readiness across European capitals. Top-performing cities combine mature infrastructure networks with comprehensive service provision, while bottom-tier cities show systematic deficiencies across multiple dimensions. Notably, the BIKE Index operates as a relative ranking system: a score of 50 represents median performance within the sample rather than an absolute benchmark.

Table 3
Descriptive statistics of the standardized BIKE Index variables after normalization.

City	FINAL VALUE	1. Infrastructure				2. Services			3. Environment			4. Safety		
		1a	1b	1c	40%	2a	2b	20%	3a	3b	20%	4a	4b	20%
		45%	45%	10%		40%	60%		60%	40%		75%	25%	
Amsterdam	60.5	84	68	42	72	62	44	51	64	37	53	55	50	54
Paris	59.6	69	61	65	65	99	66	79	56	57	56	23	61	32
Copenhagen	55.2	43	52	46	47	84	61	70	63	39	54	53	69	57
Stockholm	53.2	82	66	18	69	28	36	33	50	39	45	48	59	51
Vienna	52.8	75	52	55	63	49	51	50	53	50	52	29	58	36
Madrid	49.0	47	42	64	47	48	62	56	39	51	44	61	23	52
Brussels	49.0	50	50	61	51	60	60	60	48	39	45	29	64	38
Lisbon	47.9	52	52	66	53	61	39	48	29	72	47	52	2	39
Berlin	46.6	39	38	45	39	38	59	50	62	45	56	50	46	49
Luxembourg	44.4	50	41	24	43	38	50	45	28	31	29	64	49	61
Dublin	42.5	41	32	40	37	44	36	39	59	55	57	39	52	42
Athens	39.7	21	25	79	28	55	30	40	30	75	48	60	35	54
Rome	34.2	38	33	50	37	50	30	38	50	65	56	0	14	3
Average	49	53	47	50	50	55	48	51	49	50	49	43	45	44
Median	49	50	50	50	47	50	50	50	50	50	52	50	50	49
Max	60	84	68	79	72	99	66	79	64	75	57	64	69	61
Min	34	21	25	18	28	28	30	33	28	31	29	0	2	3

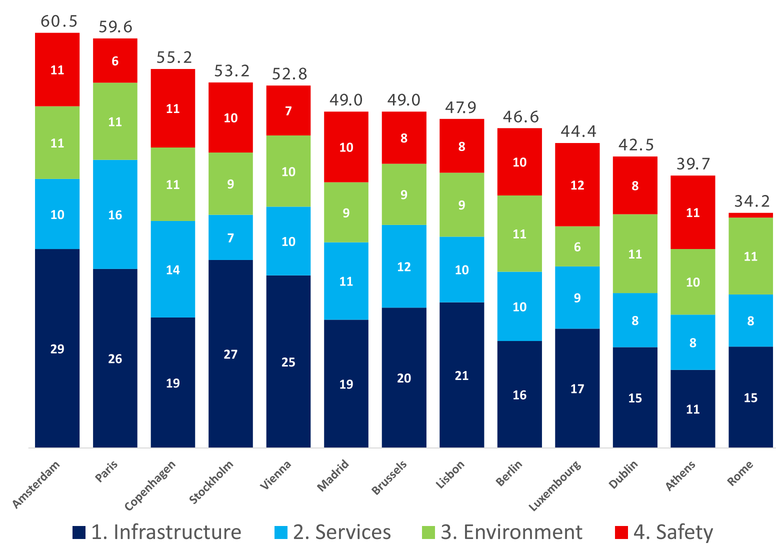

Fig. 8. BIKE Index full results, broken down by weighted dimension.

3.2. Dimension-level analysis

The results for each of the four dimensions are illustrated in Fig. 8, which shows each dimension weighted:

1. **Infrastructure Dimension (40% weight):** This dimension exhibits moderate variation (44-point range), with Amsterdam leading at 72, followed by Stockholm (69) and Paris (65). The bottom tier, Athens (28), Dublin (37), Rome (37) and Berlin (39), demonstrates fundamental infrastructure deficits that directly constrain safe cycling mobility. Berlin's unexpectedly low infrastructure score (39) suggests that cycling culture alone cannot compensate for inadequate physical networks.
2. **Services Dimension (20% weight):** Paris dominates with 79 points, followed by Copenhagen (70). This dimension shows the highest variation (46-point range) compared to infrastructure. Stockholm presents a notable paradox, scoring only 24 in Services despite achieving 78 in Infrastructure, indicating that strong physical networks do not automatically translate to comprehensive service provision. The results show that significant gaps persist in southern capitals.
3. **Environmental Constraints Dimension (20% weight):** This dimension exhibits the most compressed distribution, with scores ranging from 57 (Dublin) to 29 (Luxembourg). Most cities cluster between 45–55 points, reflecting relatively similar environmental baselines across the sample. Luxembourg emerges as a clear outlier (29 points), facing severe topographical and climatic challenges that fundamentally constrain cycling accessibility. The narrow range suggests environmental factors play a secondary role in explaining cross-city performance differences.
4. **Safety and Street Quality Dimension (20% weight):** Safety displays significant variation, ranging from 61 (Luxembourg) to 3 (Rome). Luxembourg leads despite poor performance in other dimensions, while Rome receives the most extreme score observed across all dimensions and cities. Paris scores particularly low (32) despite strong overall performance, highlighting dimension-specific challenges even among top performers. The wide spread underscores safety's critical yet uneven role across European cycling environments.

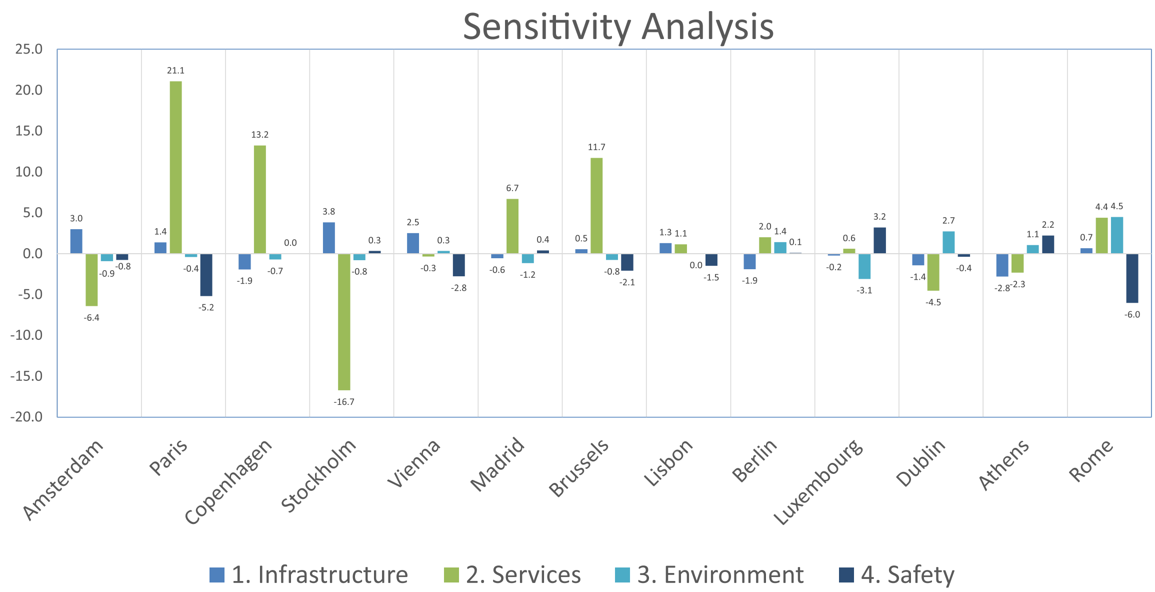

Fig. 9. BIKE Index weighting sensitivity: score shifts when one dimension weight is doubled (0.40; others 0.20) versus equal weights (0.25 each).

3.3. Cross-dimensional performance patterns

The analysis reveals distinct performance profiles among cities. Amsterdam demonstrates balanced excellence with high Infrastructure (72) and moderate scores across other dimensions. Paris exhibits service-oriented strength (Services: 70) but significant weakness in Safety (32). Copenhagen achieves consistent mid-to-high performance across all dimensions except Infrastructure.

Several cities display highly unbalanced profiles: Stockholm combines exceptional Infrastructure with poor Services, while Luxembourg pairs strong Safety with poor Environmental conditions. Rome shows consistently low performance across most dimensions, with critical Safety deficiencies. Middle-tier cities generally demonstrate more balanced profiles, with Madrid exhibiting the most balanced performance.

3.4. Sensitivity analysis

Dimension weights play a key role in determining the composite score and, therefore, the ranking. The objective of this sensitivity analysis is not to claim that the ranking is "robust" or invariant to alternative weights, but rather to make explicit how results would change under different, policy-relevant priorities and to diagnose relative strengths and weaknesses across cities.

To that end, BIKE Index scores are re-estimated under two different schemes. First, an equal-weights baseline scenario assigns identical weights to the four dimensions — Infrastructure, Services, Environment, and Safety — so that $w = (0.25, 0.25, 0.25, 0.25)$. Second, four "double-weight" scenarios are considered in which, one at a time, a single dimension receives twice the weight of each of the other three; weights are renormalized to sum to one, yielding $w = 0.40$ for the focal dimension and $w = 0.20$ for each remaining dimension. These alternatives are compared against the baseline scenario and summarized in Fig. 9.

The results of the sensitivity analysis also enhances interpretability: by doubling the weight of each dimension in turn, users can gauge the relative development of Infrastructure, Services, Environment, and Safety within each city and anticipate how the overall score would change if greater importance were assigned to any one of them. In practice, a pronounced increase (decrease) under a given double-weight scenario signals a relative strength (weakness) in that dimension.

4. Discussion

4.1. Methodological comparison with related indices

In relation to construct coverage, the BIKE Index compares favourably with prior indicators (Table 4)—Bike Score (Winters, Teschke, Brauer, & Fuller, 2016), the Propensity to Cycle Tool (Lovelace et al., 2017), the Urban Bikeability Index (Arellana, Saltarín, Larrañaga, González, & Henao, 2020), Urban Bikeability—Multifactorial (Hardinghaus et al., 2021), and Dockless-trajectory Bikeability (Wang et al., 2022)—by jointly addressing network traversability via optimal routes, protected-infrastructure coverage, route efficiency/detour, access to cyclist services and bike sharing, terrain constraints, climate suitability, safety/fatality context, and street-level design (widths, intersection treatments, surface). Several comparators capture only subsets of these elements. The BIKE Index, in addition, employs an open, standardized route-sampling protocol, offering a reproducible, multi-dimensional readiness measure suitable for cross-city benchmarking.

Beyond construct-level comparison, the discussion engages two independent, non-profit benchmarks — Clean Cities Campaign (cleancitiescampaign.org) and PeopleForBikes City Ratings (cityratings.peopleforbikes.org) — to conduct a statistical validity check centred on correlation with observed bicycle usage (Publications Office of the European Union, 2023). These benchmarks publish transparent, method-documented scores that rely primarily on public data rather than proprietary commercial inputs, offering current releases (2025), which makes possible a contemporaneous numerical comparison with the BIKE Index. Because harmonized usage statistics are available for 2023, the analysis adopts a cross-sectional design while acknowledging this modest temporal offset.

Accordingly, Fig. 10 reports cross-sectional correlations among 2023 bicycle usage, the BIKE Index, and the two external benchmarks; the BIKE Index exhibits the strongest association with observed usage, indicating superior criterion alignment relative to the comparators. However, coverage is incomplete: in the 13-city sample, both external benchmarks lack data for 4 cities (4/13), so correlations are computed on the common subset of observations; this missingness reduces statistical power and may attenuate or bias estimates, warranting cautious interpretation. Restricting the analysis to the seven cities common to all sources, the pattern persists: the BIKE Index retains the highest correlation with 2023 bicycle usage (r = 0.67), followed by Clean Cities Campaign (r = 0.58) and PeopleForBikes City Ratings (r = 0.55).

Table 4
Comparison of the BIKE Index with related frameworks.

Dimension / Variable	BIKE Index	Bike Score (Winters, 2016)	Propensity to Cycle Tool (Lovelace, 2017)	Urban Bikeability Index (Arellana, 2020)	Urban Bikeability—Multifactorial (Hardinghaus, 2021)	Dockless-trajectory Bikeability (Wang, 2024)
1a. Infrastructure type (network effectively traversable by optimal routes)	✓	✓	✕	✓	~ (self-perception)	✓
1b. Protected network coverage	✓	✓ (bike lanes, typically without explicit protection class)	✕	~ (pavement quality, not protection)	✕	✓(route type)
1c. Route efficiency / detour	✓	~ (connectivity)	✓	✓	✕	✕
2a. Access to cyclist services (workshops, parking, spare parts stores, etc.)	✓	✕	✕	✕	~ (self-perception)	✕
2b. Bike-sharing coverage	✓	✕	✕	✕	~ (self-perception)	✓
3a. Terrain difficulty (slope/hillness)	✓	✓	✓	✓	✕	✕
3b. Climate / favorable weather days	✓	✕	✕	✕ (discussed but not considered)	✕	✕
4a. Safety—fatality context	✓ (national level)	✕	✕	✓ (cyclist accidents; not normalized by bike usage levels)	✕	✕
4b. Street suitability (widths, intersection treatments, surface)	✓	✓	✕	✓	~ (self-perception)	✓
Transparency/replicability	HIGH: Open methodology with standardized route sampling and explicit weights; no proprietary inputs or behavioral outcomes mixed in.	MEDIUM: Partly proprietary recipe and weighting, and depends on region-specific datasets (surveys); documentation exists but full reproduction is constrained.	HIGH: (With limitations): Open-source code and published workflow; replicable wherever equivalent O–D and network data are available. Only England and Wales.	HIGH: Transparent multi-criteria construction (detour, slope, pavement) with clearly described data sources and steps.	LOW: Relies on survey-based, locally calibrated perceptions and facility reports, which limits strict reproducibility across contexts.	MEDIUM: (replication depends on access to operator Dockless Shared Bike trajectories and street-view imagery processing)

External validity is assessed via a correlation matrix (Table 5) that relates the BIKE Index and its sub-dimensions to two current independent benchmarks and observed bicycle usage.

The overall index correlates strongly with 2023 bicycle usage (r = 0.70) and it is consistent with the other two indexes — Clean Cities Campaign (r = 0.80) and PeopleForBikes City Ratings (r = 0.82). By dimension, Infrastructure shows the highest alignment with bicycle usage (r = 0.53). Services is strongly associated with external indicators (r > 0.7) but only moderately with bicycle usage (r < 0.3); Safety exhibits a moderate correlation with usage (r < 0.5); Environment presents weak cross-sectional correlations and a moderate inverse correlation with Safety (r = −0.47) which can be understood as milder-climate cities often lie in jurisdictions with higher national baseline fatality rates. These patterns support convergent/criterion validity of

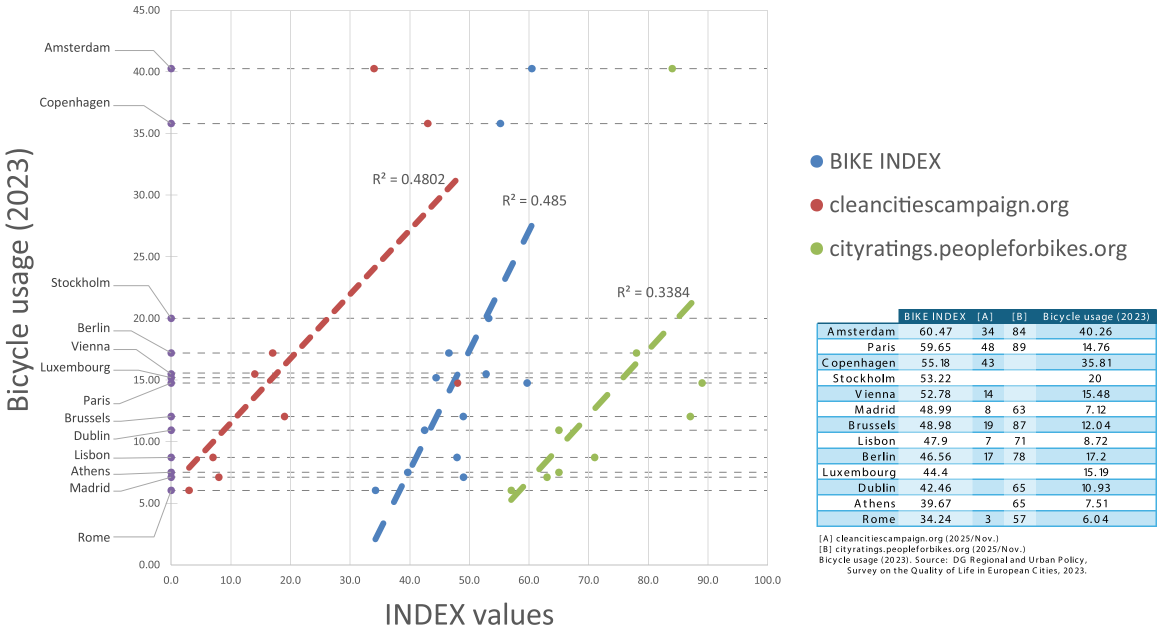

Fig. 10. Correlations with 2023 bicycle usage: BIKE Index & independent benchmarks: [A] Clean Cities Campaign (2025/Nov.); [B] PeopleForBikes City Ratings (2025/Nov.)

Table 5
Correlation matrix of the BIKE Index, its dimensions, two external indices, and 2023 bicycle usage.

	BIKE INDEX	1. Infrastructure	2. Services	3. Environment	4. Safety	[A]	[B]	Bicycle usage (2023)
BIKE INDEX	1.00	0.86	0.62	0.11	0.37	0.80	0.82	0.70
1. Infrastructure	0.86	1.00	0.28	0.03	0.07	0.52	0.73	0.53
2. Services	0.62	0.28	1.00	0.18	0.06	0.84	0.76	0.30
3. Environment	0.11	0.03	0.18	1.00	-0.47	0.42	0.02	0.16
4. Safety	0.37	0.07	0.06	-0.47	1.00	0.41	0.27	0.45
[A]: cleancitiescampaign.org	0.80	0.52	0.84	0.42	0.41	1.00	0.83	0.69
[B]: cityratings.peopleforbikes.org	0.82	0.73	0.76	0.02	0.27	0.83	1.00	0.58
Bicycle usage (2023)	0.70	0.53	0.30	0.16	0.45	0.69	0.58	1.00

the index while underscoring that correlations do not imply causation; data heterogeneity, single-year outcomes, and data scarcity, warrant cautious interpretation.

4.2. Fulfilment of study objectives and contributions

This research has fully met its four stated objectives and delivers three key contributions:

- **Open-Data, Reproducible Methodology**: The BIKE Index is built entirely on publicly available sources: OpenStreetMap, OpenRouteService (Neis, Dietze, & Zipf, 2007-01), Eurostat, Copernicus, and employs robust, transparent computational workflows. No qualitative or subjective variables were used, ensuring that the framework is scalable to any city or time without reliance on proprietary data.
- **Multi-Dimensional, Policy-Relevant Framework:** By integrating infrastructure, services, environmental constraints, and safety into a single composite measure, the BIKE Index provides a novel tool for evidence-based decision-making. Its route-based assessment captures real cycling conditions, while visual outputs translate complex data into actionable insights for urban planners.
- **Comparative Insights Across and Within Cities:** Beyond the methodological innovation, a central contribution of this research is the ability to generate systematic cross-city comparisons as well as intra-city analyses. This dual perspective allows benchmarking between urban areas while also highlighting strengths and weaknesses within each city across the different dimensions of the index.

Together, these achievements position the BIKE Index as both a rigorous academic contribution and a practical decision-support tool to guide investments that foster safer, more equitable, and more sustainable cycling environments.

4.3. Limitations of the study

While the BIKE Index offers a robust and reproducible framework for assessing urban cycling conditions, several limitations must be noted. The study relies heavily on open, crowd-sourced data sources such as OpenStreetMap and Google Maps, which can vary in completeness, accuracy, and consistency across cities due to differing mapping conventions and update frequencies. In particular, OpenStreetMap information is maintained by a volunteer-based community, making its quality and detail dependent on the activity and engagement of local contributors. This variability could affect the reliability of infrastructure and service coverage variables.

Variations in urban perimeter definitions across cities introduce comparability challenges: some boundaries encompass dense urban cores, while others include broader metropolitan or suburban zones. For example, Paris's LAU (Local Administrative Unit) was limited to its central municipality, elevating density measures compared to cities with expansive boundaries. This variation may bias coverage-based variables and complicate cross-city comparison.

The index incorporates proxy variables when direct data are unavailable, for instance, using national-level cyclist fatality rates as surrogates for city-level safety, which may misrepresent actual local risks. The fixed weighting scheme (40% infrastructure, 20% each for services, environment, and safety) assumes uniform importance across contexts and allows strong performance in one dimension to offset weaknesses elsewhere, potentially masking critical gaps. Since fatality proxies are measured at the national level their representativeness of intra-national heterogeneity in traffic conditions, or local contexts is limited. This may simplify city-specific conditions into a single jurisdictional value. Therefore safety score has to be interpreted as a contextual baseline, while city-level differences in network design and operating environment are represented in other dimensions of the BIKE Index.

While external validation against observed outcomes (e.g., cycling mode share, usage statistics, or user-reported "bikeability") is desirable, robust cross-city comparisons remain constrained by heterogeneity in definitions, spatial coverage (city vs. functional urban area), survey instruments, and update cycles. Other studies are limited and uneven availability of commuter-level modal-share data across cities and ad hoc measurement practices, which hinder like-for-like correlation tests across jurisdictions. Moreover, because mode share is a behavioural outcome shaped by socio-demographic and policy factors, it is not a direct measure of network "readiness"; current evidence shows that inter-city "bikeability" aligns more closely with infrastructure-quality metrics than with usage or satisfaction measures. Notwithstanding these limitations, BIKE index top-ranked cities are consistently recognized in independent sources for strengths aligned with our index's constructs—providing qualitative face validity consistent with (but independent from) our findings.

Finally, the study focuses on 13 European capitals to hold macro-institutional conditions relatively constant (EU policy framework, data standards) while ensuring substantial internal heterogeneity in size, topography, climate, cycling culture, and network form. This sampling strategy was chosen to test the methodology under a comparable regulatory environment and to reveal cross-city differences through the BIKE Index, not to claim representativeness of all global contexts. In particular, the approach relies on open, harmonized datasets (e.g., street networks, cycling facilities, elevation, climate, and service locations) whose coverage and quality are uneven in some countries, specially in cities of the Global South. Extending, calibrating, and externally validating the BIKE Index in non-European contexts is identified as a priority for future research.

4.4. Future research directions

Possible future works lie in building upon the BIKE Index as a foundation for continued methodological development. The index could serve as a solid base for expansion—incorporating additional dimensions such as political commitment, cycling culture, or traffic stress—and for longitudinal studies to track policy impacts over time. This potential underscores the value of the framework not only as a static tool, but also as a platform for iterative refinement and broader applications.

Future studies should expand the BIKE Index application to a larger and more diverse set of cities across Europe and globally, enabling broader benchmarking and identifying context-specific factors shaping cycling conditions. A comprehensive sensitivity analysis of methodological choices, including normalization methods, weighting schemes, and aggregation formulas, would enhance robustness and transparency.

Standardizing urban perimeter definitions based on functional urban areas or built-up zones can improve inter-city comparability and mitigate boundary-induced biases. Incorporating additional qualitative and policy-related dimensions, such as political commitment, cycling culture, financial investment, and experiential metrics like traffic stress, would enrich the index and capture the full spectrum of factors influencing cycling success.

Transitioning the BIKE Index to a longitudinal framework will enable monitoring of trends over time, evaluation of policy impacts, and adaptive management of urban cycling environments. By addressing these limitations and pursuing methodological refinements, the BIKE Index can evolve into a comprehensive, adaptable, and policy-relevant tool supporting sustainable urban mobility planning worldwide.

5. Conclusions

This study presents the BIKE Index as a reproducible, multi-dimensional measure of urban cycling readiness grounded in open data and a standardized route-sampling protocol. The framework integrates four conceptually distinct dimensions—Infrastructure, Services, Environment, and Safety—weighted according to actionable leverage, with Infrastructure receiving greater emphasis due to its direct modifiability through local planning, investment, and design standards.

The BIKE Index yields a clear hierarchy of cycling readiness across the 13 capitals. The ranking is led by Amsterdam (60.5), Paris (59.6), Copenhagen (55.2), Stockholm (53.2), and Vienna (52.8); a middle tier includes Madrid, Brussels, Lisbon, Berlin, Luxembourg, and Dublin (≈42–49), while Athens (39.7) and Rome (34.2) lag behind. Leaders pair high infrastructure scores with adequate services and non-penalizing environment/safety values; e.g., Paris is service-intensive, Copenhagen and Stockholm are infrastructure-forward, and Vienna is balanced. Mid-ranking cities display uneven composition—Madrid and Brussels reach similar totals via different mixes (safety vs. services)—whereas Lisbon and Berlin are constrained primarily by infrastructure. Lower-ranked cities exhibit pronounced infrastructure and service deficits, with Rome showing the lowest safety scores.

Empirically, the composite index exhibits strong criterion alignment with observed bicycle usage and convergent validity with two independent external benchmarks. A weighting sensitivity analysis—contrasting equal-weights and "double-weight" scenarios—demonstrates how alternative policy priorities would reallocate scores, thereby enhancing interpretability and revealing relative strengths and gaps across cities rather than asserting weight-invariant rankings.

Taken together, the BIKE Index offers a transparent, transferable framework for diagnosing cycling readiness, comparing cities on a common basis, and informing investment priorities. By unifying infrastructure, services, environment, and safety within an open, standardized methodology, the index provides a practical tool for evidence-based planning while delineating a clear agenda for future validation and refinement.

CRediT authorship contribution statement

Alejandro Quintero Gómez: Writing – original draft, Validation, Software, Formal analysis, Data curation, Visualization. **Pablo Calvo-Bascones:** Writing – review & editing, Supervision, Methodology, Conceptualization, Data curation, Visualization.

Declaration of competing interest

The authors declare that the submitted manuscript is original and has not been published previously, nor is it under consideration for publication elsewhere. All authors have read and approved the final version of the manuscript and agree with its submission to Sustainable Cities and Society. The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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