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Rethinking Bikeability Indexes: Fusing Knowledge Graph and MCDA Technique for Multi-criteria Bike Network Evaluations

Ayda Grisiute [1] and Martin Raubal [1]

[1]Institute of Cartography and Geoinformation, ETH Zurich, Zurich, Switzerland

Correspondence: Ayda Grisiute (agrisiute@ethz.ch)

Abstract.
The evaluation of bike networks is important for improving cycling infrastructure and supporting sustainable travel behaviors. While bikeability indexes are widely used, current methods typically rely on straightforward metric aggregation, often overlooking nuanced interactions between evaluation elements. In this study, we introduce a novel approach to integrate a Knowledge Graph (KG) of bikeability evaluation studies with the Analytic Network Process (ANP), a decision modeling technique. The KG, which comprises more than 270 bikeability metrics and 41 qualitative criteria, provides a structured foundation for index development, reflecting the trends in existing evaluation approaches. ANP enhances this framework by capturing the interdependencies in the use of qualitative criteria and quantitative metrics, ensuring a more rigorous and transparent aggregation process. As a case study, we apply this methodology to Zurich's road network and evaluate network bikeability at the segment level. Further, we conduct a sensitivity analysis of how changes in the KG structure impact the network evaluation results. By treating bikeability index development as a decision-making task, our study strengthens the methodological foundation of bikeability index design. Future research will scale this framework to larger networks, extend the sensitivity analysis, and benchmark our approach against established bikeability indexes.

Submission Type. Model, Analysis

BoK Concepts. [AM5-7] Multi-criteria evaluation

Keywords. Analytic Network Process, Active Mobility, Spatial Decision Modeling

1 Introduction

A robust evaluation of bike networks is crucial to assess their effectiveness and plan new infrastructure (Grisiute et al., 2024). Various methods evaluate the expected cycling quality based on infrastructure, traffic, safety, and environmental factors. Among these, bikeability indexes are widely used to coherently integrate multiple existing metrics and criteria (Ahmed et al., 2024). Although significant effort has been made to identify and select relevant metrics based on literature reviews and urban analytics, less attention has been paid to how these metrics are integrated into a single index.

Existing bikeability indexes often use survey-based metric weighting, expert-determined classification schemes, or domain-specific methods such as cost-benefit analysis, as summarized by Grisiute et al. (2024) and Ahmed et al. (2024). However, the implications of how individual metrics interact within the index (e.g., their compensatory effects or information transfer) are rarely addressed. Designing effective bikeability assessments requires transparent decisions about how metrics are derived, weighted, and aggregated.

To address this challenge, we propose a novel bikeability index design that integrates a graph database of bike network evaluation studies (Grisiute et al., 2024), with a multi-criteria decision analysis (MCDA) technique. MCDA provides a formal framework for structuring and solving complex decision problems involving multiple, often conflicting criteria (Malczewski and Rinner, 2015). We achieve this by using a Knowledge Graph (KG), which compiles bike network metrics and qualitative criteria from 25 academic studies, with the Analytic Network Process (ANP), an MCDA technique specifically designed to model interactions and feedback loops between decision elements.

As a case study, we apply this methodology to Zurich's road network and perform a sensitivity analysis on the impact of the KG structure on the results of the bikeability index. By systematically assessing these influences, our approach strengthens the methodological foundation for bike network evaluations.

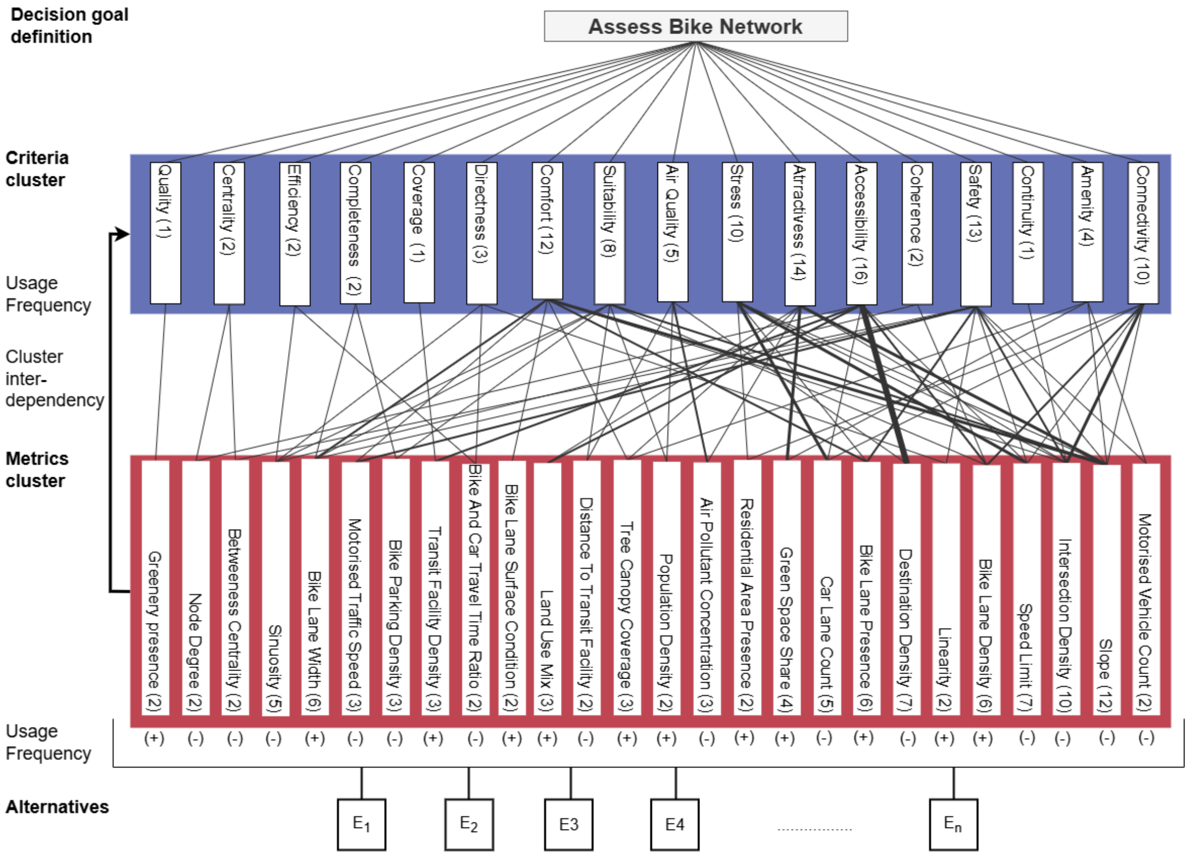

Figure 1. Overview of bikeability metrics and qualitative criteria extracted from the KG. The figure illustrates the frequency of metrics used in bike network evaluation studies and their corresponding qualitative criteria as well as positive or negative contribution to bikeability.

2 Background

This section reviews the current landscape of bikeability indexes, highlighting both their common design patterns and key gaps. We also discuss how index modeling approaches using MCDA can address these gaps and improve the overall decision-making process in bike network evaluations.

2.1 Approaches to Modeling and Aggregating Bikeability Indexes

Bikeability indexes are typically designed by integrating various data sources to derive specific metrics and linking these metrics to qualitative criteria that reflect public objectives (Grisiute et al., 2024). This integration reflects a collective understanding of what constitutes an effective bike network by blending various perspectives into a cohesive framework.

Two key steps are common in a bikeability index design: (1) selecting which metrics to integrate and how to measure them, and (2) determining an appropriate method for aggregating these metrics into a single index. The first step has been extensively studied, with clear trends emerging (Ahmed et al., 2024). For example, Weikl and Mayer (2023) and Grisiute et al. (2024) have systematically identified common evaluation metrics for bike networks. The latter developed a Knowledge Graph (KG), a graph-based database, containing over 270 metrics from 25 bike network evaluation studies. Using the VeloNEMO ontology, this KG formally organizes metrics by qualitative criteria, spatial aggregation features, units, and thematic categories.

However, the second step is more ambiguous. The aggregation of metrics in bikeability indexes is often based on methods such as weighted linear combination (WLC) (McHenry and Rinner, 2016) or decision trees (Mekuria et al., 2012), which have notable limitations. WLC may not account for compensatory effects, where infrastructure improvements cannot fully compensate for the negative effects of high traffic or noise pollution. Similarly, although decision tree-based indexes can potentially simplify interpretation, they risk oversimplifying complex relationships.

2.2 Leveraging MCDA for Bikeability Evaluations

Multicriteria decision analysis (MCDA) investigates modeling decisions and the interplay of criteria and stakeholder preferences in the evaluation of alternatives (Cinelli et al., 2020). Although domain agnostic, MCDA is widely ap-

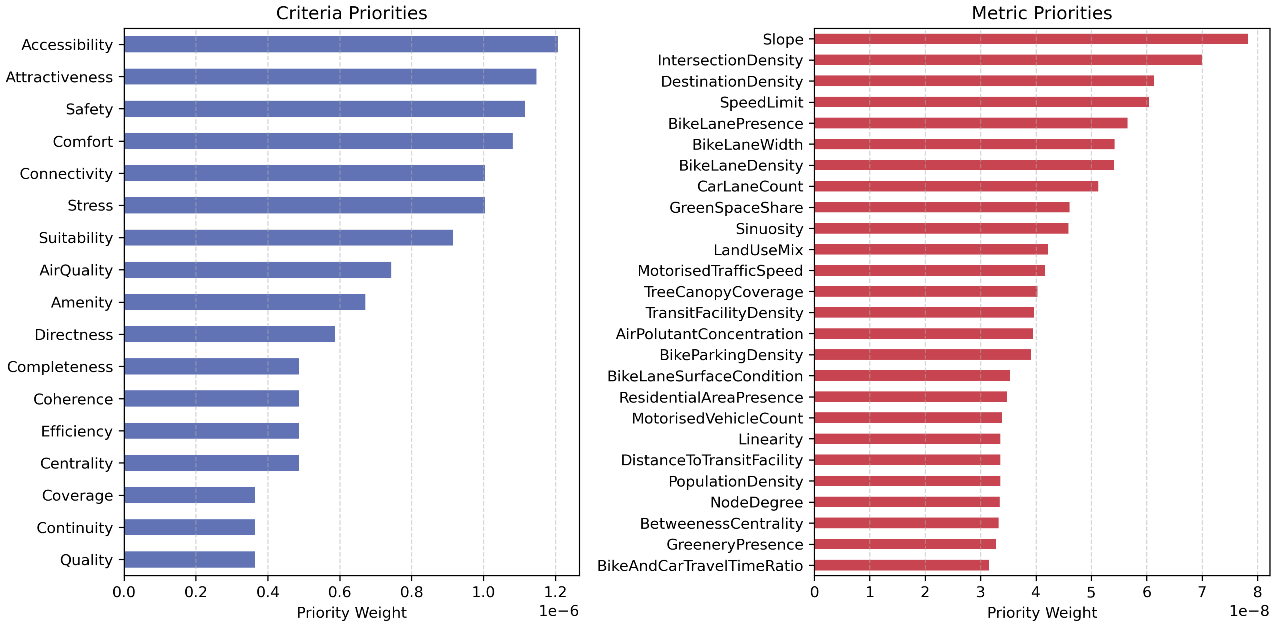

Figure 2. Priority vectors for metrics and criteria derived from our KG-MCDA workflow. The figure illustrates the relative importance of each evaluation element in the final bikeability assessment, highlighting the most influential metrics and qualitative criteria based on the pairwise comparison process.

plied in spatial contexts (Malczewski and Rinner, 2015), including evaluations of bike networks (Lin and Wei, 2018; Zuo and Wei, 2019; Zagorskas and Turskis, 2020; Terh and Cao, 2018; Pais et al., 2022; Hsu and Lin, 2011; Güldü et al., 2024), with the Analytic Hierarchy Process (AHP) being the most common technique. AHP hierarchically decomposes criteria and assigns importance weights based on pairwise comparisons provided by stakeholders. The process involves comparing two criteria at a time, using a numerical scale (1-9) to express the preference strength. In an AHP hierarchy, elements at one level influence those below them.

However, when applied to bikeability indexes, AHP can overlook the interdependencies between qualitative criteria and quantitative metrics. For example, Grisiute et al. (2024) notes that the semantics of criteria, as defined by the linked metrics, can overlap, complicating the distinction of unique criteria. Furthermore, the easy retrieval of metrics can lead to their frequent use across criteria, further blurring the line between individual criteria. These challenges suggest that alternative methods, such as network-based decision models, can better capture the complex relationships between the evaluation components in bikeability indexes.

The Analytic Network Process (ANP), a generalization of the AHP, models decision problems as networks that capture feedback loops and interdependencies (Saaty, 2016; Taherdoost and Madanchian, 2023). Unlike AHP's hierarchy, ANP allows mutual influence between metrics and criteria. ANP employs supermatrix operations to synthesize pairwise comparisons, a process Saaty compares to a Markov chains due to their use of matrix representations and stochasticity (Malczewski and Rinner, 2015). The supermatrix consists of submatrices that represent relationships between different clusters (criteria and metrics). These relationships are explicitly captured in the KG with the VeloNEMO ontology, allowing a straightforward integration of the KG and ANP. For a detailed explanation of the KG design, please refer to Grisiute et al. (2024).

3 Methods

This section outlines our methodology for developing a bikeability index for Zurich's road network. We begin with data acquisition and preparation, using a KG to select relevant metrics and enriching the network with contextual information. Next, we describe the implementation of our ANP-based approach to derive a segment-based bikeability ranking. Finally, we present the initial sensitivity analysis for our approach.

3.1 Data Acquisition and Preparation for Bikeability Index Development

Bike Network Evaluation Metrics. The bikeability metrics used in this study were derived from the KG developed by Grisiute et al. (2024), which compiled 25 global bicycle network evaluations (detailed in Section 7). Each study in the KG, structured using the VeloNEMO ontology, represented usage relationships between metrics, criteria, and other evaluation properties, while also capturing various metric preferences across studies. Metrics used fewer than twice or unsupported by Zurich's data were excluded from

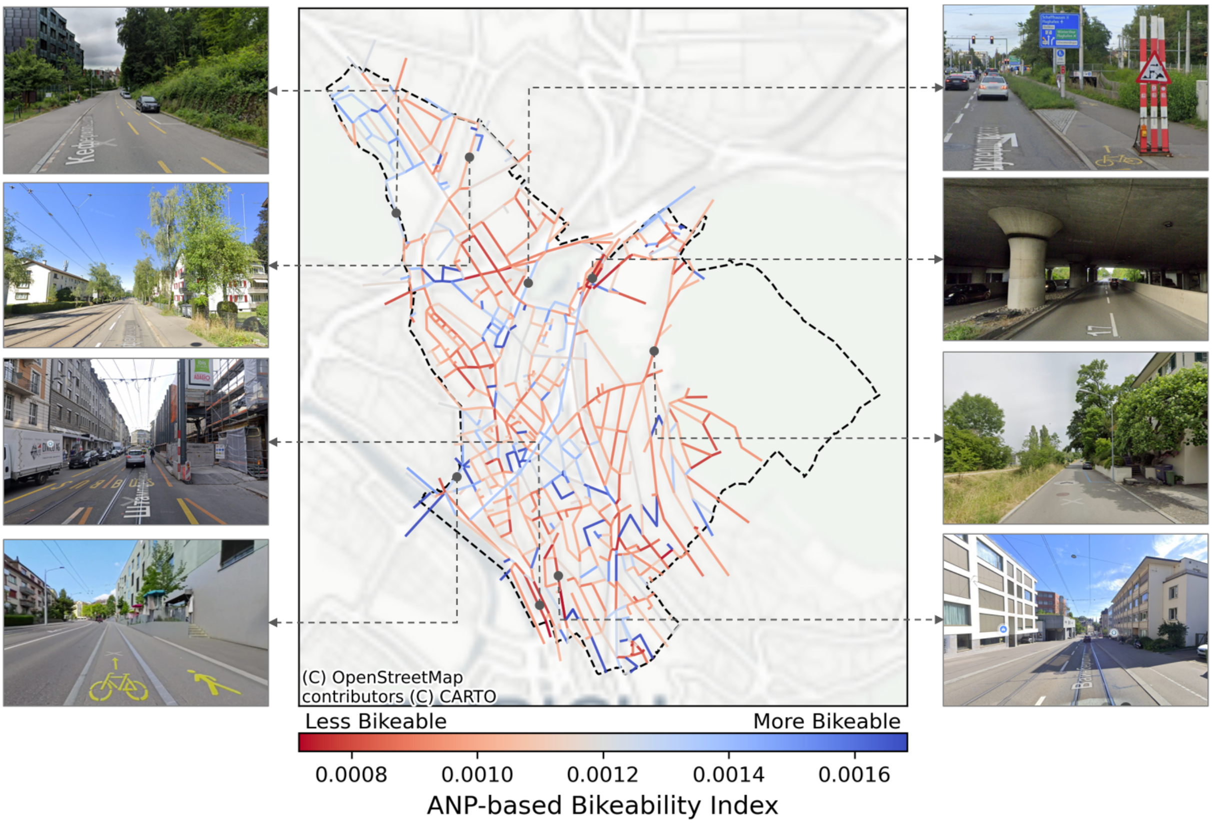

Figure 3. Spatial distribution of the Bikeability Index across Zurich's District 6 road network. The map visualizes the relative prioritization of road segments based on our methodology integrating infrastructure, traffic conditions, environmental factors and so forth. Higher index values indicate more bike-friendly segments.

further workflow. Figure 1 presents the final list of interconnected metrics and criteria, along with their frequencies, which we used as proxies for the metric preference strength in the ANP model.

Road Network. We pre-processed the Zurich road network into a simplified structure following the methodology of Ballo et al. (2024). Each network segment was enriched with metric values derived from contextual data sources (e.g., population, noise pollution, traffic volume). Metric values were normalized to a consistent range to ensure an equal effect in the ANP, regardless of their original scales or units. Furthermore, the outlier values across attributes were remapped to the 95th percentile prior to integration into the ANP framework to prevent distortion of pairwise comparisons by outliers.

3.2 Analytic Network Process Model Construction

To assess bikeability using ANP, we structured the decision problem with the goal of assessing the bikeability of the Zurich road network segments. The model incorporated key criteria, each associated with specific evaluation metrics (see Figure 1). In this framework, the segments of the road network served as alternatives (the entities compared).

To account for bidirectional dependencies, where metrics influence criteria and vice versa, we incorporated feedback loops, transforming the traditional hierarchical structure of AHP into a network. For example, metrics like slope can influence multiple criteria (e.g., safety, comfort) due to their relevance in different aspects of bikeability. We captured this influence in the ANP framework by allowing metrics to affect the weighting of criteria through additional pairwise comparisons. For example, the impact of the slope metric on safety and comfort can be compared by analyzing the respective criteria frequencies.

The decision model is represented by a supermatrix that integrates pairwise comparisons between criteria, metrics, and alternatives with the general structure introduced in Section 2.2. Figure 1 illustrates the full list of elements used. Due to the complexity of applying ANP to large-scale networks (more than 10,000 segments), we initially implemented our approach in a single district of Zurich with almost 900 segments. Even within this smaller area, the number of alternatives far exceeded the typical counts in MCDA applications, remaining the main challenge of our model. The initial unweighted supermatrix W is structured as follows:

$$W = \begin{bmatrix} W_C & W_{CM} & 0^{c\times a} \\ W_{MC} & W_M & 0^{m\times a} \\ 0^{a\times c} & W_{AM} & I^{a\times a} \end{bmatrix}$$

where $W_C \in [0,1]^{c\times c}$ represents influences between criteria, $W_{CM} \in [0,1]^{c\times m}$ and $W_{MC} \in [0,1]^{m\times c}$ capture metric-criteria interactions and vice versa, $W_M \in [0,1]^{m\times m}$ denotes influences between metrics, $W_{AM} \in [0,1]^{a\times m}$ reflects metric-alternative relationships and finally $I \in [0,1]^{a\times a}$ is the identity matrix.

Criteria and metric influences are computed by pairwise comparison of frequencies:

$$W_{\{C,M\}} = \begin{bmatrix} 1 & \frac{f_1}{f_2} & \cdots & \frac{f_1}{f_n} \\ \frac{f_2}{f_1} & 1 & \cdots & \frac{f_2}{f_n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{f_n}{f_1} & \frac{f_n}{f_2} & \cdots & 1 \end{bmatrix}$$

where f_i represents the frequency in the KG of the criteria or metric, respectively, which serves as a proxy for the preference strength.

The metric-criteria and criteria-metric interactions are computed as follows:

1. For each criterion (or metric), construct a pairwise comparison of frequencies P between metrics (or criteria) similar to W_M (or W_C) but limited to the frequency under the criterion (or metric).

2. Compute the priority vector $\mathbf{w}$ as eigenvector of P corresponding to the maximum eigenvalue $\lambda_{\max}$:

   $$P\mathbf{w} = \lambda_{\max}\mathbf{w}$$

3. Use the normalized priority vector $\mathbf{w}$ as column of matrix W_{MC} (or W_{CM}).

To ensure logical consistency in pairwise comparisons, the Consistency Ratio (CR) was checked and confirmed to be between 0 and 0.1 for all pairwise comparison matrices. A CR below 0.1 indicates acceptable consistency in pairwise comparisons, while a CR above 0.1 suggests inconsistency that requires revision (Malczewski and Rinner, 2015).

Next, we constructed W_{AM}, which compares alternatives based on the actual metric values associated with the segments. Before storing them as a matrix, all metric values were normalized to ensure the same value range $[0,1]$, with some metric ranges inverted according to their positive or negative impact on bikeability (e.g. *Slope* and *AirPollutantConcentration* negatively affect bikeability) (see Figure 1). The direction of these effects was based on the study description in the KG.

Finally, the weighted supermatrix W^* was created by the following normalization:

$$W^*(i,j) = \frac{W(i,j)}{\sum_j W(i,j)}$$

where $W(i,j)$ represents the original unweighted value in row i and column j, and $\sum_j W(i,j)$ is the sum of all values in column j. This normalization ensured that each column sums to one, which is required for ANP computations. The final limit supermatrix W^∞ was obtained by iteratively raising W^* to higher powers until convergence:

$$W^\infty = \lim_{k\to\infty} (W^*)^k$$

where the steady state values in W^∞ define the final bikeability index for the chosen road network.

3.3 Sensitivity Analysis Design

Sensitivity analysis is a crucial step in MCDA, as it allows us to evaluate how variations in input (Bottero and Ferretti, 2010), specifically changes in the KG structure, affect the final results. This variation in metric and criteria inclusions is rarely applied in bikeability assessments.

To systematically assess the robustness of our approach, we implemented two sensitivity analyses: (1) criterion permutation, where individual criteria (along with associated metrics) are removed and the KG and bikeability index is recalculated, and (2) metric permutation, where individual metric types (along with linked criteria instances) are removed from the KG before recomputing the index. These permutations allowed us to define an expected error interval that quantifies the variation in road segment bikeability. Assuming a normal distribution, we define this interval as the 95% confidence range (± 2 standard deviations), representing the range within which the bikeability value of a segment is expected to fall.

4 Results

In this section, we present the results generated from our KG-MCDA integration for developing a bikeability index. First, since the limit supermatrix W^∞ for Zurich *District 6* has dimensions 922×922, we focus on presenting the priority vectors only for metrics and criteria (see Figure 2). These vectors highlight the most influential evaluation elements (criteria and metrics), aligning with the trends observed in previous studies (Ahmed et al., 2024; Grisiute et al., 2024; Weikl and Mayer, 2023). For example, *Sinuosity* and *GreenSpaceShare* occur five times in the KG, but are weighted differently since the latter is related to *Attractiveness* (a more influential criterion).

Figure 3 illustrates the spatial distribution of the bikeability rankings across network segments, showing how the chosen combination of factors shapes the final index and

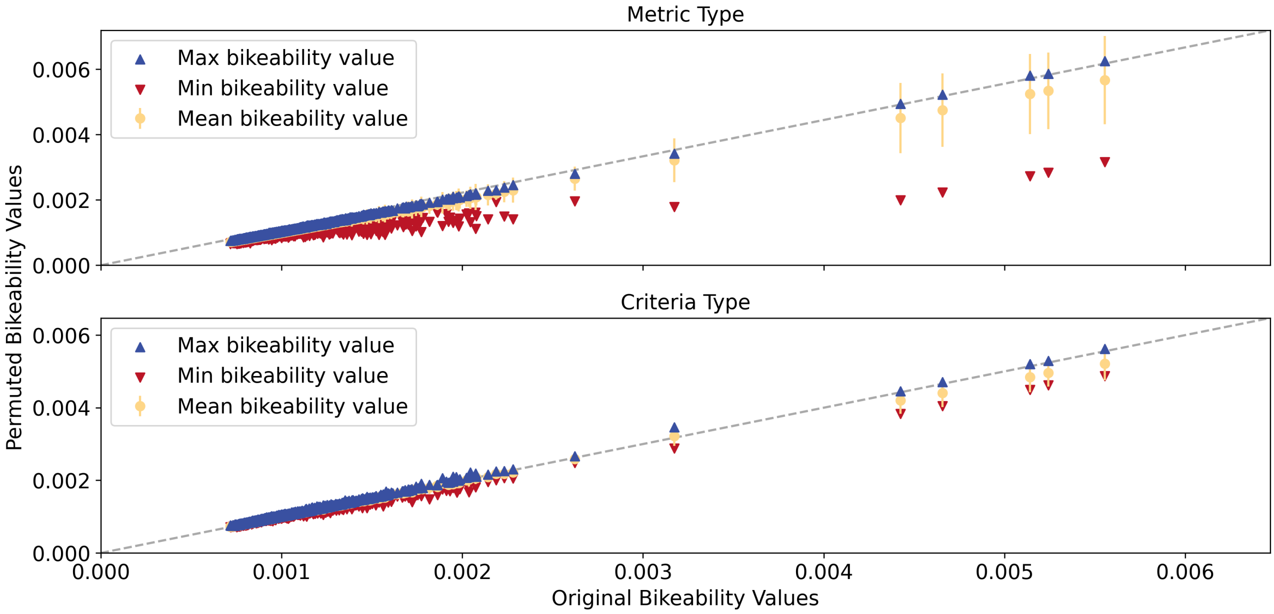

Figure 4. Sensitivity Analysis of Bikeability Index. The top panel illustrates the impact of removing individual metric types on bikeability scores, while the bottom panel shows the effect of removing individual criteria types. Each point represents a segment's bikeability score after permutation, with blue triangles indicating maximum, red inverted triangles indicating minimum, and yellow circles representing mean bikeability score. Yellow error bars indicate the expected variability in bikeability scores due to permutations.

highlighting the variations in bikeability throughout the network. Since our focus is on structuring the aggregation of criteria and metrics into a cohesive framework, we do not analyze specific bikeability values in detail. However, we spot-checked several segments with the corresponding street views for consistency. A more comparative evaluation of the performance of our approach would require benchmarking it against existing bikeability assessment methods.

Finally, we analyzed the sensitivity of our bikeability index with respect to the structure of the KG. First, we removed individual criteria types (and associated metrics) and recalculated bikeability scores. Figure 4 shows how each permutation affects bikeability at the segment level, allowing us to define expected error intervals relative to the original values. The second analysis followed the same approach, but we removed individual metric types (and associated criteria) before recalculating the bikeability index. The variation in scores increases with the original bikeability value, particularly in the case of metric permutation where some metric removal results in significantly lower bikeability scores. For criteria permutation, the mean bikeability index remains relatively stable, with minimum and maximum values fluctuating within the expected error interval. This highlights that highly bikeable segments are more sensitive to metric exclusions than to criterion exclusions. This is likely because bike network evaluations typically contain more metrics than criteria. Removing metrics leads to greater weighting changes, as more elements are excluded from the KG.

5 Discussion

This study introduces a novel approach to developing a bikeability index by integrating a KG of existing bike network evaluations with the ANP technique. ANP models interactions among the evaluation elements, while the KG provides a comprehensive knowledge base with commonly used evaluation criteria linked to quantitative metrics. To our knowledge, no previous MCDA application for bike network evaluations has addressed the interdependence between metrics and criteria, making this integration a promising direction for future research.

Our approach offers a transparent, data-driven workflow for eliciting criteria and metrics for bikeability index development, as opposed to manual literature reviews that are commonly used. In addition, the proposed methodology can handle a large number of alternatives, almost 900 road segments, which can be repeated throughout the Zurich road network. By defining the expected error interval in our sensitivity analyses, we established a systematic framework to evaluate the impact of changes in the KG structure on bikeability rankings while accounting for varying selection of evaluation criteria and metrics. We demonstrated how a KG can be integrated with a formal decision-structuring method to address a critical, yet often overlooked, component in bikeability index design.

Despite these contributions, several limitations remain. Additional sensitivity analyses are needed, e.g., to determine whether different spatial scales (such as nodes, zones, or grids) for segment enrichment adequately support certain metrics. In addition, the inherent ambiguity in linking metrics to criteria, where a single metric can influence multiple criteria or vary in naming, requires further investigation. For example, membership functions could be tested to better capture qualitative vagueness and address overlapping indicators (e.g., *green space share* versus *greenery presence*) to avoid potential double counting. Finally, our model currently assumes compensatory effects, where factors such as high greenery can offset poor road surface quality. While this approach is common in many bikeability indexes, it may not reflect real-world evaluation processes and could be reconsidered with non-compensatory aggregation methods.

In summary, integrating KG with ANP provides a viable framework to build generic bikeability indexes. The results underscore the need to assess interdependencies, accommodate varying evaluation preferences, and utilize research-based knowledge to derive metric and criteria weighting.

6 Conclusions and Future Outlooks

In this study, we developed an ANP-based bikeability index by integrating MCDA with a KG, containing various approaches to evaluate bike networks. We proposed an initial framework to systematically structure relevant bike network metrics and qualitative criteria, effectively capturing the complex interdependencies among various bikeability factors. Using a KG, which synthesizes extensive research, our methodology organizes a large body of scientific work and trends in bike network evaluations into a coherent structure.

Future work will extend this framework to the entire Zurich road network, expand the KG, and conduct further sensitivity analyses to validate the robustness of the index. We will focus on refining this methodology, exploring alternative aggregation techniques, and benchmarking our index against other established bikeability evaluation frameworks. These steps will improve the utility of our bikeability index, supporting informed decision-making for the development of urban cycling infrastructure.

7 Data and Software Availability

The research data supporting this publication are available on Zenodo and are accessible via the following DOIs: spreadsheet of bike network evaluations that were used to repopulate the KG, the road network and related contextual data for metric estimation (https://doi.org/10.5281/zenodo.14839760). The computational workflow supporting this publication is published on GitHub with instructions included in the file *README.md* in the following repository: https://github.com/mie-lab/anp_bike_network_evaluation.

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Declaration of Generative AI in writing

The authors declare that they have used Generative AI tools to improve grammar, sentence structure, and LaTeX formatting. All intellectual and creative work, including the analysis and interpretation of data, is original and has been conducted by the authors without AI assistance.

Author contributions. **Ayda Grisiute**: Conceptualization, Methodology, Writing - Original Draft, Visualization, Software; **Martin Raubal**: Writing - Review & Editing, Supervision, Funding acquisition.

Competing interests. The authors declare that there are no competing interests.

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