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Bikeability assessment using machine learning and user survey

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ABSTRACT

Urban areas face multiple challenges stemming from population growth and the limited capacity of transportation systems. Sustainable transport modes, such as cycling, are crucial for addressing congestion, pollution, and accessibility. Bike infrastructure improves overall accessibility but accessibility also depends on actual and perceived safety and comfort. To measure these nuanced aspects, a broader indicator is needed. Bikeability aims to bridge this gap. It can be approached in two different but complementary ways. Either quantitatively through objective measurements or simulations (e.g., type of infrastructure, slope, speed and traffic) or qualitatively.

This paper proposes a hybrid, reproducible framework that combines quantitative and qualitative aspects. Using five indicators based on open data (type of infrastructure, slope, speed of motorized traffic, number of lanes and environment), a user survey and machine learning, we propose a bikeability assessment model. Results from our decision tree model show that physical separation is the primary factor defining bikeability, splitting the remainder of the model into a safety-focused branch and a comfort-focused branch. Cyclists prioritize aesthetics and comfort only after basic infrastructure separation guarantees safety. Validated through a case study of Lyon, France, the results show a high correlation between top-rated segments and the most frequented biking spots in the city. This framework provides urban planners with a scalable, low-cost diagnostic tool to prioritize infrastructure investments without relying on expensive sensing campaigns.

1 INTRODUCTION

Cycling is increasingly promoted as a sustainable urban transport mode because it reduces greenhouse gas emissions and air pollutants while providing significant health benefits. Moreover, cycling infrastructure is typically more space-efficient than car-oriented infrastructure. In dense urban areas characterized by short travel distances and scarce space, it contributes to congestion mitigation and the efficient allocation of public space.

Despite this momentum, evaluating the quality of cycling conditions remains challenging. Existing approaches often lack a robust and replicable framework that can be applied across different cities, largely due to heterogeneous data availability and the lack of a generalized standard measure. One of the primary metrics used to evaluate cycling networks is accessibility. However, accessibility for bikes is (i) difficult to define and (ii) encompasses both qualitative and quantitative aspects, such as perceived safety and comfort. These considerations motivate the use of the broader concept of *bikeability*. A widely accepted operational definition is still missing in the literature. We adopt the following definition [1]:

“Bikeability refers to the degree to which an area is conducive to safe, convenient, and enjoyable cycling transportation. It encompasses various factors that affect the ease, connectivity, and safety of cycling, making it a practical mobility option for both commuting and recreational purposes. Bikeability represents an assessment of the cycling level of service in terms of the ability and experienced convenience and comfort to access diverse destinations.”

Existing bikeability assessment methods span several methodological families (see the recent meta-analysis in [2]). At one end of the spectrum, granular measures, such as vibration or roughness indices, quantify cycling conditions through pavement-related measurements collected with sensor-equipped bicycles [3]. While precise at the segment level, dedicated sensing campaigns remain difficult to scale or replicate across entire networks.

A second family comprises Bicycle Level of Service (BLOS) models. BLOS methods typically map roadway and traffic attributes to a score, which is then interpreted as a letter grade (A to F). In [4], the BLOS score is calculated by summing four adjustment factors that account for distinct attributes: geometric characteristics, traffic conditions, roadway context, and pavement condition. Another widely used methodology family relies on computing a Bikeability Index (BI), which aggregates diverse indicators, such as safety and attractiveness, to produce a bicycle-friendliness measure. Several multi-factor indices have been proposed [5, 6, 7]. For example, Grigore et al. [5] model bikeability using a cost-multiplier function; this involves adding costs associated with infrastructure slope, infrastructure type, and various hazards while subtracting benefits derived from the environment and aesthetics.

Finally, safety-focused approaches, such as the Bicycle Safety Index (BSI), rely primarily on traffic flows and modal interactions, often combined with crash data, to quantify potential safety issues. For instance, Daraei et al. [8] combine a bicycle-accident dataset with street-feature data to assess safety across multiple cities.

A common limitation across these families is the difficulty of transferring models between contexts due to discrepancies in data coverage, definitions, and measurement procedures.

Complementary to these quantitative approaches are perception-based methods such as stated preference studies using surveys and interviews, and revealed preference studies conducted through field observations. In France, the Bike User Federation¹ (FUB) conducts a nationwide survey to evaluate perceived bike-infrastructure quality [9]; similar surveys exist in other countries. Another line of research categorizes cyclist types [10, 11, 12] and investigates socio-economic determinants, such as gender, age, income, and place of residence—that influence perceived bikeability. While informative, these approaches can be difficult to replicate at scale and often require substantial time and resources.

This methodological diversity underscores the complexity of assessing bikeability. While indicator-based methods are more objective, they frequently overlook the nuances and heterogeneity of human preferences (e.g., age, gender, and fitness level). Conversely, qualitative methods capture these nuances but remain difficult to replicate or scale across entire urban networks. Furthermore, many existing approaches are either difficult to transfer across cities due to data constraints and heterogeneous definitions, or they fail to explicitly model perceived safety and comfort. In this article, we propose a hybrid approach that integrates quantitative indicators with user perception, as defined by [1]. The proposed approach encompasses various factors affecting the *ease, connectivity, and safety* of cycling; it explicitly links levels of service to perceived safety and comfort, integrating these components within a single assessment pipeline. We first use open-data to measure characteristics of infrastructures. Then we use a survey to verify and assess how people perceive the connection between these measures and actual bikeability. Finally we use a machine-learning model trained on the measurements and the survey results to enable large-scale automated bikeability assessments.

The main contributions of this paper are as follows:

- A parsimonious set of readily available indicators, balanced for interpretability, transferability, and data availability, measured using extensive open-source geospatial data.
- A reproducible hybrid framework that combines a stated-preference survey with a machine-learning model to estimate perceived bikeability and validate the scoring scheme.
- A proof-of-concept application to the city of Lyon, France, demonstrating the end-to-end workflow, from survey design to network-wide scoring.

2 METHODOLOGY

This section introduces the proposed reproducible framework for estimating *perceived* bikeability across an urban street network. The objective is to assign a bikeability grade to each network edge by combining (i) readily available, interpretable infrastructure and context indicators with (ii) user-perception data.

The proposed framework consists of three main components:

1. Indicator measurement: computing the indicators for each road segment of the network.
2. Survey component: collecting stated preferences and ratings for representative cycling scenarios.

¹Fédération des Usagers de la Bicyclette

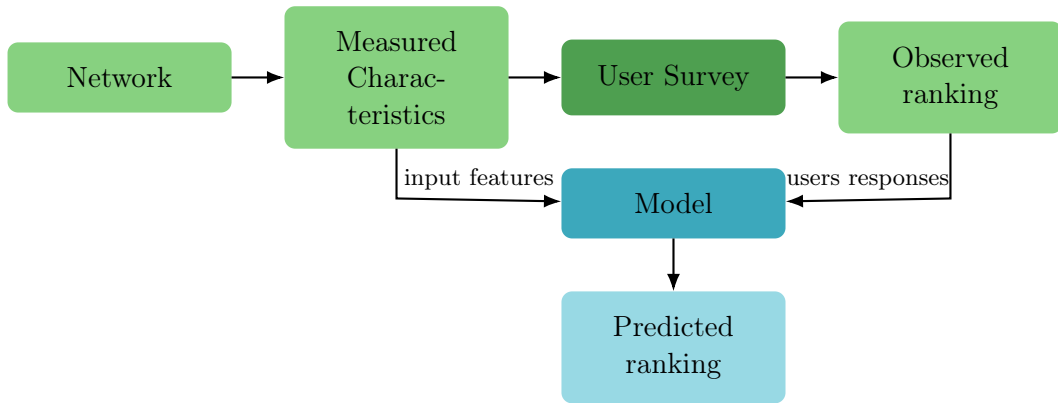


Figure 1: Machine learning framework

3. Machine-learning component: learning a mapping between measurable indicators and perceived bikeability scores, then applying this model to the entire network.

The main strengths of this design are (i) *transferability*, as it relies on a small set of indicators that can be derived from widely available datasets; (ii) *interpretability*, because the chosen model and inputs can be inspected and correspond directly to human perception and decision-making; and (iii) *scalability*, as the final scoring step is applied automatically to all network edges and can be easily replicated for other cities. Figure 1 summarizes how these methodological steps relate to one another to provide the final bikeability measurement.

Network Indicators Processing

We employ four indicators, selected from the literature to balance availability, interpretability, and the coverage of both objective and subjective dimensions of bikeability:

Cycling infrastructure type

This indicator distinguishes between shared vs. non-shared facilities with other vulnerable road users, and separated vs. non-separated facilities from motorized traffic. We rely on the infrastructure definition given by the data source, as detailed in Table 1. We differentiate two primary characteristics, *separation* and *sharing*. Separation indicates whether a physical barrier exists between cyclists and motorized traffic. Sharing defines whether the infrastructure is used concurrently with other vulnerable road users, such as pedestrians. These characteristics are encoded using a 0 to 3 scale.

Slope

This represents the gradient of the road segment. Using topography data, we classify segments into three categories: no slope, light slope and steep slope. We calculate the slope of every 10-meter road segment as follows : $slope(\%) = \frac{z_B - z_A}{d_{AB}} \times 100$ and aggregate the results for the entire road segment.

Motor-vehicle traffic

This indicator is measured directly when available or approximated using proxies such as the number of motorized lanes and posted speed limit. We utilize four categories for speed and exact number of lanes.

Environment and aesthetics

This indicator captures exposure to green spaces and bodies of water. We calculated the overlap of these areas within a 10-meter buffer around each road segment. The percentage of green and water space is processed as: $green(\%) = \frac{A_{overlap}}{A_{buffer}} \times 100$. These indicators are further detailed in Table 2.

Survey design

The survey component elicits users’ perceptions of the bikeability of infrastructure segments and the relative importance they attribute to specific characteristics. Because perceived safety and

Type of infrastructure	Examples
Non-separated and shared	residential streets, shared-space
Non-separated and non-shared	bike-lanes
Separated and shared	walkways, pedestrian area, green-ways
Separated and non-shared	bike-path

Table 1: Characterization of different type of bike infrastructure Shared or non-shared with other vulnerable road users and separated or non-separated from motorized traffic.

Features	Study	Measurement	Categories
Type of infrastructure	[13, 14, 15, 16, 17]	Based on BDTOPO classification	See Table 1
Slope	[13, 15, 16]	Using topography data	no slope (0% to 10%); >10%
Number of lanes	[14, 15, 16, 5]	Based on BDTOPO	1; 2; >3
Speed of motor-traffic	[14, 15, 16, 5]	Based on speed	<20 km/h; 20-40 km/h; >40 km/h
Environment and aesthetics	[18, 19, 20, 21]	Green and water space coverage	<25%; 25% to 50%; >50%

Table 2: Features used to compute bikeability measurement.

comfort are inherently subjective and context-dependent, the survey is designed to be adaptable to different cities and inclusive of both cyclists and non-cyclists. The survey consist of the following components:

Socio-demographic information

The first section collects socio-demographic data from respondents, including age, gender, place of residence, occupation, cycling frequency, trip purpose, and bicycle type, to assess their influence on individual preferences.

Infrastructure rating

In the second section, participants are presented with a series of images depicting road segments and cycling facilities under varying traffic conditions, each accompanied by a short description. These photographs, taken on-site, are selected to cover diverse conditions regarding infrastructure type, slope, surrounding environment, and motor-vehicle traffic. They are used to capture the impacts of these variables on people’s choices and preferences. Each photograph is associated to a set of measured characteristics. Respondents rate each photograph on a 1–5 scale (1: “I would absolutely avoid cycling there”; 5: “I would feel safe and comfortable cycling there”). These ratings then serve as a proxy for perceived bikeability.

Relative importance evaluation

The third section estimates the relative importance of the considered characteristics using Best–Worst Scaling (BWS) [22]. Respondents answer 10 questions; each presenting three characteristics; the respondent must select the most and the least important factors influencing their willingness to cycle.

The results are then processed as follows. Let B_k and W_k denote the number of times characteristic k is selected as most and least important, respectively, and let f be the number of times characteristic k is presented (in this study, $f = 6$). The BWS score² for characteristic k is computed as:

$$BWS_k = \frac{B_k - W_k}{f}. \quad (1)$$

The resulting BWS_k ranges from $[-1, 1]$ (where -1 represent the least important feature and 1 the most important feature) and reflects the relative perceived importance of each characteristic.

Machine Learning framework

The final component of the framework processes the survey results to develop a model that learns to rank and assess perceived bikeability based on the measured characteristics as input features and the ratings provided by the respondents as the target to predict. This model generalizes

²A balanced BWS design requires that each distinct pair of characteristics appears an integer number of times. With t characteristics and k characteristics per question, this value is $\lambda = \frac{f(k-1)}{(t-1)}$. In our case, $t = 5$, $k = 3$, and $\lambda = 3$.

the survey findings to the entire network and potentially to other cities. The dataset consists of the measured characteristics of the survey, namely infrastructure type, slope, motor-vehicle speed, number of lanes and green space overlap, paired with their corresponding mean user ratings (on the 1–5 scale). We employ an 80/20 train-test split for model development. A *decision-tree* model [23] was selected to approximate user perception, as it is robust when working with smaller datasets and offers high interpretability. Following the training phase, we compare the model’s features importance with the BWS outcomes to verify consistency between the learned weights and the stated preferences. Finally, we use the inferences of the trained model to rank unseen cycling facilities and, ultimately, to the entire network.

3 CASE STUDY

In this section, we present the results of a practical application of our framework to the city of Lyon, France. This proof of concept utilizes the BDTOPO database [24], an open-source, high-quality geospatial dataset maintained by the IGN³; equivalent databases are available in many other countries.

Survey Results

The survey was developed using Google Forms and distributed primarily through ENTPE⁴ general mailing list. We obtained 220 responses over a three-week period. Due to the distribution method, the majority of respondents were students (75.5%), aged under 24 (74.1%), and residing within the Lyon metropolitan area (77.5%). Most respondents cycle daily (60.2%) and own a bicycle (80.0%), typically a city bike (36.4%), road bikes (34.1%), or mountain bikes (29.5%). We observed near gender parity, with 51.8% of respondents identifying as male and 45.9% as female.

The results of the BWS framework are displayed in Figure 2. The type of cycling infrastructure was identified as the most important feature (BWS = 0.73), which aligns with the existing literature. Furthermore, the results indicate that the motor-vehicle speed and the number of motorized traffic lanes are the next most important characteristics, with BWS scores of 0.39 and -0.26, respectively. These findings suggest that when considering traffic-related factors, vehicle speed has a greater impact on perceived bikeability than the number of lanes. Finally, the surrounding environment (BWS = -0.34) and road slope (BWS = -0.52) were identified as the two least important characteristics for the respondents. These rankings are compared with the machine learning framework outcomes in the following section.

Machine Learning Results

We utilized a decision tree model [23] to simulate the human decision-making process. The dataset consists of 17 items ($n = 17$), each evaluated by the 220 survey responses. Each item represents a specific cycling scenario characterized by its characteristics and its corresponding mean rating. These characteristics and rating are detailed in Table 3, where mean rating serve as the ground-truth labels. We implemented a regression tree model, which predicts a continuous value and is well-suited for estimating mean grades. However, this approach requires normalization and rounding to obtain the final categorical grade. The regression model achieved a Mean Squared Error (MSE) of 0.000 with the training set and a MSE of 0.120 on the test set (using 14 item for training and 3 for testing). Additionally, a Leave-One-Out (LOO) cross-validation yielded an MSE of 0.035. The case study presented in the following section uses the regression tree result shown in Figure 3.

The regression tree (depth = 7) reveals several insights into users’ bikeability perceptions. As evidenced by the root node of the tree, the number of lanes is the most critical parameter. This indicator serves as a proxy for the separation aspect mentioned in section 2. Beyond the root node, the tree divides into two branches:

- Comfort (Left branch): Here, the presence of greenery and the slope are emphasized. Since physical separation from traffic provides users with a higher feeling of safety, user’s evaluation shifts toward aesthetic and comfort-related aspects.

³*Institut national de l’information géographique et forestière*, french national cartography agency.

⁴ENTPE (French National School of Civil Engineering) hosts the laboratory, and its students and staff represent a readily accessible test group.



Figure 2: Best-Worst Scores for characteristics tested in the survey.

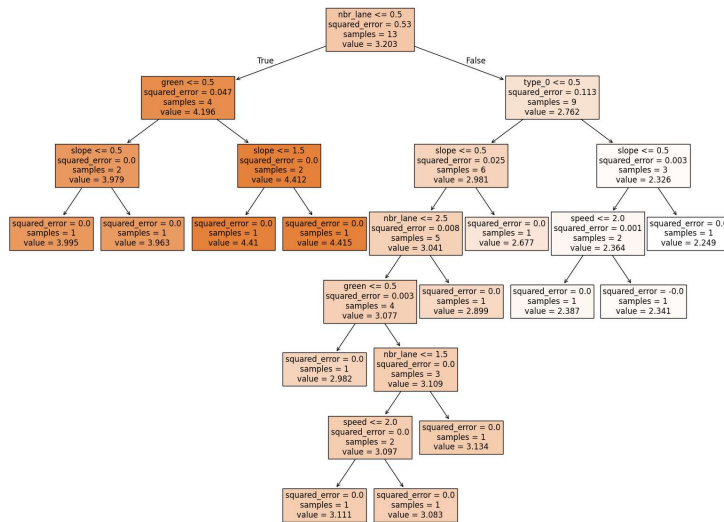


Figure 3: Regression Decision tree model

photo	average rating	median rating	standard deviation
1	4,627	5	0,653
2	4,109	4	0,905
3	3,118	3	0,899
4	2,391	2	0,932
5	4,005	4	0,995
6	3,877	4	1,020
7	2,264	2	0,990
8	2,982	3	0,876
9	3,955	4	0,997
10	3,082	3	0,867
11	4,414	5	0,809
12	2,341	2	1,196
13	3,127	3	1,056
14	2,891	3	1,001
15	2,668	3	1,057
16	2,027	2	0,960
17	4,405	5	0,814

Table 3: Survey results summary.

- Safety (Right branch): Where there is no separation between cyclists and motor vehicles, the user focus shifts toward safety rather than comfort. The tree distinguishes first between the presence of a bike lane versus no infrastructure, highlighting that specific infrastructure, even if minimal, is preferred. Then other traffic-related indicators are utilized. Greenery is notably absent from this branch, as the focus is purely on safety.

This dichotomy highlights that physical separation is a rigid prerequisite before environmental comfort factors become relevant to users.

The model results are partially aligned with the survey’s BWS score (Figure 2). Infrastructure separation aspect is the most important factor in both methods. However, a significant divergence emerges regarding traffic-related indicators. Based on the regression tree, the number of lanes and speed indicators are less decisive (depth of 6 and 7) than the BWS score suggests. This discrepancy underlines the value of the hybrid approach: what users explicitly state they prioritize in abstract surveys often differs from how they subconsciously evaluate real-world contextual scenarios.

Bikeability computation

In this final section, we present the results of the case study as a proof of concept for our framework. We chose the network of Lyon, France, as the study area, as the city is currently developing an extensive network of bicycle paths. First, calculated all required characteristic for every edge of the network using the BDTOPO dataset [24]. To apply the trained model and obtain coherent ratings across the network, we normalized the model output, where 2.249 is the minimum value (corresponding to a grade of 1) and 4.415 is the maximum value (corresponding to a grade of 5), and rounded the results to the nearest integer. This normalization is a necessary outcome of using a regression-tree model. The spatial result are presented in Figure 4, and the distribution of grades is shown in Figure 5. Overall, the most popular and frequented biking spots received high ratings by the model. For example *VL1* (fully separated high quality bike lane near the river) or paths inside parks are rated as 5. While the model tends to slightly overestimate grades compared to the survey, the results remain consistent with survey insights and finding of previous literature. We observe that the distribution of grades is not homogeneous. Specifically, there is a high concentration of edges rated as 1, 4, or 5, with almost no edges receiving a 2 or 3; this is inconsistent with the original survey results. We attribute this polarization to a lack of granular training data representing shared, intermediate urban spaces. This reveals a critical insight for urban modeling: accurately reflecting human compromise requires highly stratified data targeting these ‘edge-case’ transitional infrastructures.

Further observations were made by manually assessing specific road segments. Major separated



Figure 4: Map of Lyon bike network with modeled rating.

infrastructures are correctly rated as 5. Major motorways (e.g., the *M6* and *M7*, which have 70 km/h speed limits, three lanes in each direction, and no cycling infrastructure) are correctly rated as 1. However, some urban boulevards, such as the *Cours Franklin Roosevelt* (with a 50 km/h speed limit, three lanes in one direction, and a painted bike lane) are also rated as 1. In contrast, the survey results indicate that users gave this specific infrastructure a grade of 3 (see photo 13). This discrepancy likely stems from a lack of motorway examples in the training dataset, causing the model to penalize multi-lane urban roads as severely as high-speed motorways. Future work should incorporate a more diverse range of infrastructures, including high-capacity roads, to improve model accuracy.

4 SUMMARY AND CONCLUSIONS

The machine learning and survey-based approach presented in this study provides a scalable and readily interpretable network-level assessment of bikeability. We have proposed an innovative framework to rate and evaluate cycling infrastructure using indicators derived from existing literature and widely available data. Ultimately, this framework provides urban planners with a scalable, low-cost diagnostic tool to identify network weak links and prioritize infrastructure investments without relying on expensive sensing campaigns.

Nevertheless, improvements could be made in future work. Model accuracy could be enhanced by including a more nuanced classification for infrastructure types. Furthermore, selecting a more diverse set of survey photographs could have provided greater precision—specifically regarding the

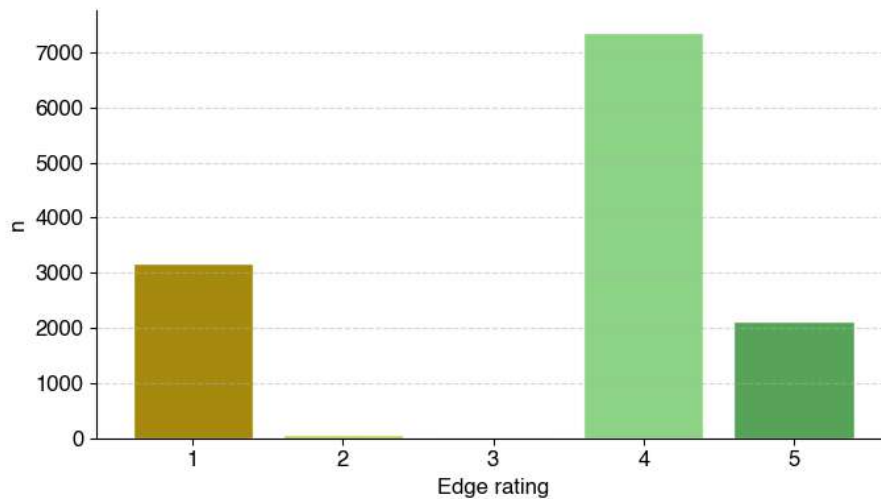


Figure 5: Histogram of the grade of edges of the Lyon bike network.

distinctions between high-speed motorways and multi-lane urban boulevards. While the choice of a five-point grading scale was intended to facilitate user understanding and simplify the survey, it remains a limitation that restricts the granularity of the results. Despite these constraints, the model successfully represented the relative importance of the subjective aspects of perceived safety and comfort required to accurately summarize bikeability.

The weight of subjective bikeability factors and the rigorous quality assessment of geospatial databases should be focal points for future research. Furthermore, refining the selection and parameterization of the machine learning model could lead to even more precise and realistic bikeability assessments. By leveraging specific socio-demographic clusters, future work could generate profile-specific network maps (e.g., 'family-friendly' versus 'experienced commuter'), aiding users dynamically adjust routing based on varied risk tolerances.

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