The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, Volume XLVIII-4/W10-2024
8th International Conference on Smart Data and Smart Cities (SDSC), 4–7 June 2024, Athens, Greece

Safety Assessment of Cycling Routes in Urban Environments

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KEY WORDS: Cycling route; Safety assessment; Urban environment; GIS; Smart mobility

ABSTRACT:

As one of the most well-known forms of active mobility, cycling is an environmentally friendly way to explore a destination, becoming increasingly prevalent worldwide. However, safety is the most severe issue facing cyclists and the essential factor for people who are hesitant to use bikes. In this context, we propose a safety assessment method for cycling routes in urban environments. This work presents how to automatically generate a safe cycling map integrating volunteered geographic information with GIS analysis. We start by extracting the indicators that can possibly contribute to cycling safety from OpenStreetMap. Then, we set up a multivariate linear regression equation to solve the importance of indicators. Afterward, we generate a weighted graph model that represents cycling safety. Taking the City of Bonn, Germany, as an example, we implement our approach for this region. The experiment results show that Bonn is a city for safe cycling, confirming the claim that Bonn is a bike-friendly city. Our findings can also be used to plan the safest route for cycling, thereby enhancing the overall biking experience in Bonn.

1. INTRODUCTION

With the pressure of urbanization and population boom, cycling provides an eco-friendly and affordable alternative to cars or public transportation and has the benefits of decarbonizing road transport, reducing air and noise pollution, and easing traffic congestion (Pucher and Buehler, 2017; Sun et al., 2020; Ding et al., 2021; Meng and Zheng, 2023). However, cyclists are often required to switch between different lanes, and safety is deemed critical as it can directly impact the well-being of cyclists who share the road with other vehicles, which is also one of the essential factors in converting car drivers or public transportation users to bike users in commuting (Daraei et al., 2021a; Panagiotaki et al., 2024).

Generally, city planners and policy makers can use the safety assessment of cycling routes to identify areas that need improvement regarding cycling infrastructure and safety measures (Schepers et al., 2014). In general, there are three ways of assessing the cycling route's safety: actual, perceived, and inferred safety. Actual safety directly estimates the risk of cycling through data on accidents, fatalities and bicycle trip counts. Perceived safety assesses the risk through user surveys and provides a subjective view. Inferred safety infers the risk through indirect measures, for example, the relative position or speed of motor vehicles to bicycles when there is no direct measure available (Daraei et al., 2021a). Subsequently, some open data, e.g., OpenStreetMap (OSM), and new techniques, e.g., GIS analysis, have been used for safety or bikeability assessment (Ito and Biljecki, 2021; Wysling and Purves, 2022).

To our best knowledge, there is much research on bikebility assessment, but no composite index exists to assess the cycling route's safety. From the authors' point of view, the study for the safety assessment of cycling routes in urban environments should answer the following questions:

1. How to extract the indicators that can possibly contribute to cycling safety?
2. How to quantify the importance of considered indicators?
3. How to establish the weighted graph model that represents cycling safety?

In this context, we propose a safety assessment method for cycling routes in urban environments. The aim is to provide safe routes for cyclists and also improve their internal drive for active mobility. Figure 1 shows exemplarily the resulting map assessing the safety of cycling routes for the city of Bonn in Germany. A higher score indicates a lower grade of safety.

The remainder of this paper is structured as follows: Section 2 introduces the related work. Section 3 gives insights into the introduced approach. Section 4 discusses the experimental results. Section 5 summarizes the paper and gives an outlook for future research.

2. RELATED WORK

Worldwide, cities play a key role in social and economic aspects, while having a crucial impact on the environment (Mori and Christodoulou, 2012). As of 2021, more than half of the global population (approx. 56%) lived in cities, with this number expected to increase to roughly two-thirds (approx. 68%) by the year 2050 (UN, 2022). However, as of today most energy worldwide is consumed in cities, with the largest amount being consumed for electricity and transportation, contributing to a poor environmental performance of cities (Mori and Christodoulou, 2012). Regarding Europe, urban mobility generates more than 40% of total CO_2 emissions (Riccardo Mangiaracina and Tumino, 2017). In this context, cycling, besides public transportation, is a sustainable form of urban mobility and transportation without impacting the environment as much as

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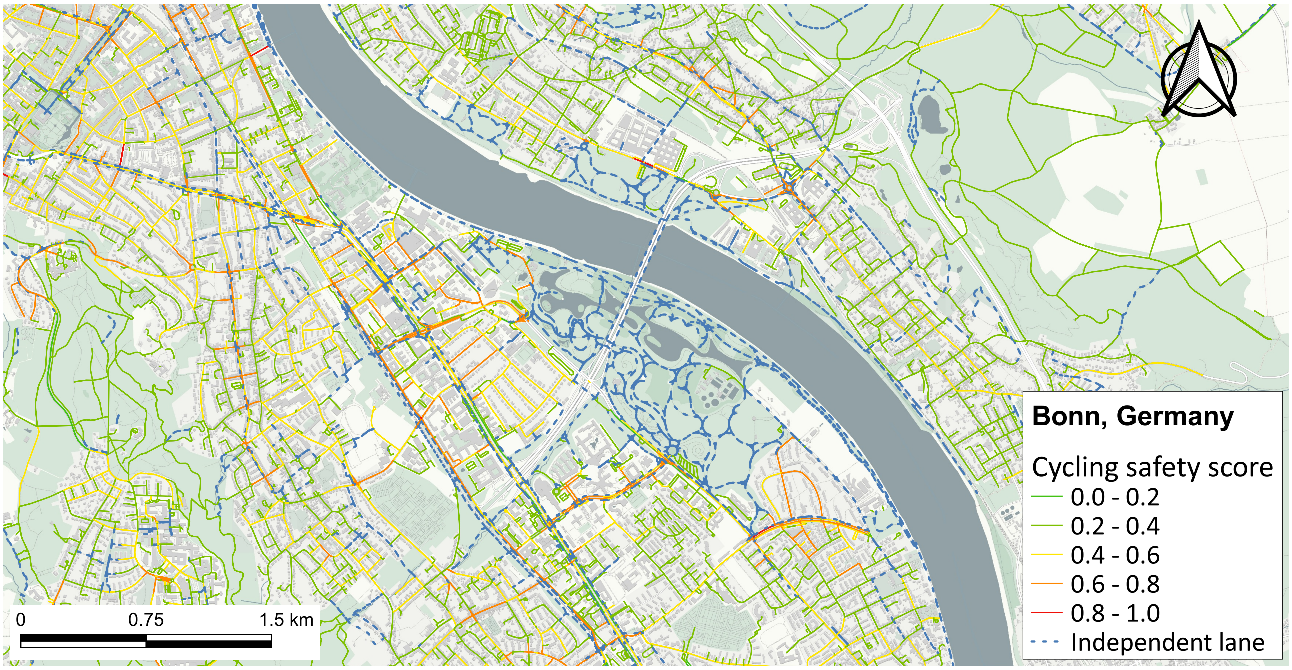

Figure 1. Safe cycling routes of Bonn, Germany. Higher scores mean less safety.

motorized individual transport (Behrendt, 2019). However, besides cars, other road users commonly found in urban areas, e.g., trucks used for freight transport and cargo or buses and trams used for public transportation, add negative effects on the cyclist's safety (Riccardo Mangiaracina and Tumino, 2017; Daraei et al., 2021a).

Smart cities are urban areas that utilize digital technology, e.g., the Internet of Things (IoT), to provide real-time information on traffic conditions (Vito Albino and Dangelico, 2015) or to enhance urban services, e.g., public transportation by developing algorithms for individually tailored routing algorithms (de Oliveira e Silva et al., 2022) and visualization techniques (Arzoumanidis et al., 2023; Forsch et al., 2021). Furthermore, to promote sustainable and environmentally friendly development, new governance tools, e.g., for engaging citizens through digital platforms or provide transparency in decision-making are desired (Vito Albino and Dangelico, 2015). Emerging topics are in this context Mobility Digital Twin (MDTs) (Wang et al., 2022) and Driver Digital Twin (DDT) (Schwarz and Wang, 2022). A DDT represents a virtual environment to model human drivers by digital counterparts. This allows for reflecting driver behaviors and driving patterns and, hence, making decisions and predictions building upon (Fan et al., 2022; Schwarz and Wang, 2022).

Accommodating the needs of active mobility, e.g., cycling, is essential for the transition towards a sustainable urban mobility. In this context, safety is a key factor influencing cyclist behavior. Thus, investigating how safety is perceived can support urban planning that in return will attract more cyclists (Gössling and McRae, 2022a). Regarding the assessment of safe cycling, different methods have been proposed. Recently, Panagiotaki et al. (2024) investigated how the road infrastructure influences cyclist safety by collecting data about different traffic scenes captured using a custom-designed helmet of sensors. In contrary, Daraei et al. (2021b) utilized cycling accident data to model cycling safety based on geographical and infrastructural features. However, their approach is not able to assess the safety for individual cycling routes, potentially hindering the application for cyclists city-wide. A more related approach has been recently published by Beil et al. (2023). The authors performed an automatic evaluation of the service quality of bicycle paths. In this context, they extracted features like the width of the cycle lane from a semantic 3D city model in CityGML exchange format.

3. METHODOLOGY

The first step is to select a set of indicators contributing to cycling safety, as shown in Table 1. Some of the indicators were selected with reference to the Level of Traffic Stress (LTS), which classifies the components of a road network according to the stress experienced by cyclists (Szyszkowicz, 2018; Huertas et al., 2020). Obviously, the traffic stress of cyclists is highly related to the number of lanes, speed limits, the types of lanes, etc. Figure 2 shows the relationship between different lane types and the degree of protection afforded to cyclists (Roughton et al., 2012).

In addition, our methodology requires a road network model in the form of graph $G = (V, E)$ as input, the ultimate goal is to determine an edge weighting $\omega : E \to R \geq 0$ that assigns to each edge $e \in E$ a weight $\omega(e)$. An edge e represents an abstraction of a road segment in the underlying real network. Specifically, this work involves selecting indicators and computing weights of edges to assess the cycling route's safety at the city level.

The overview of the work process is shown in Figure 3. First, we derived the indicator values $x \in X$ from OSM (OpenStreetMap, 2024) data and subsequently normalized them to lie between 0 and 1. Following this, a subset of samples was labeled with a-priori scores $\hat{y}$ determined by cycling expertise. Second, we set up a multivariate linear regression equation, the above equation is solved using the least squares to obtain an estimate of θ_i, which represents the contribution of each indicator to cycling route's safety as can be shown in equation 1:

Table 1. List of the considered indicators in our study.

Number	indicators		Description	Values
1	Max speed		Maximum speed allowed on a road segment	$\frac{v_{\max}}{100}$
2	Number of lanes		Number of lanes on a road segment	$\frac{n-n_{\min}}{n_{\max}-n_{\min}}$
3	Parking allowed		Whether parking is allowed on a road segment	1 or 0
4	Incident to crossing		Whether a road segment is incident to a crossing	1 *or* 0
5	Lane type	Safety lane	A dashed lane on a motorway with priority for cyclists	1 *or* 0
		Cycle lane	A lane for cyclists only on a motorway	1 *or* 0
		Separated lane	A lane is separated from motorway	1 *or* 0
		Shared lane	A lane is shared with motorway	1 *or* 0

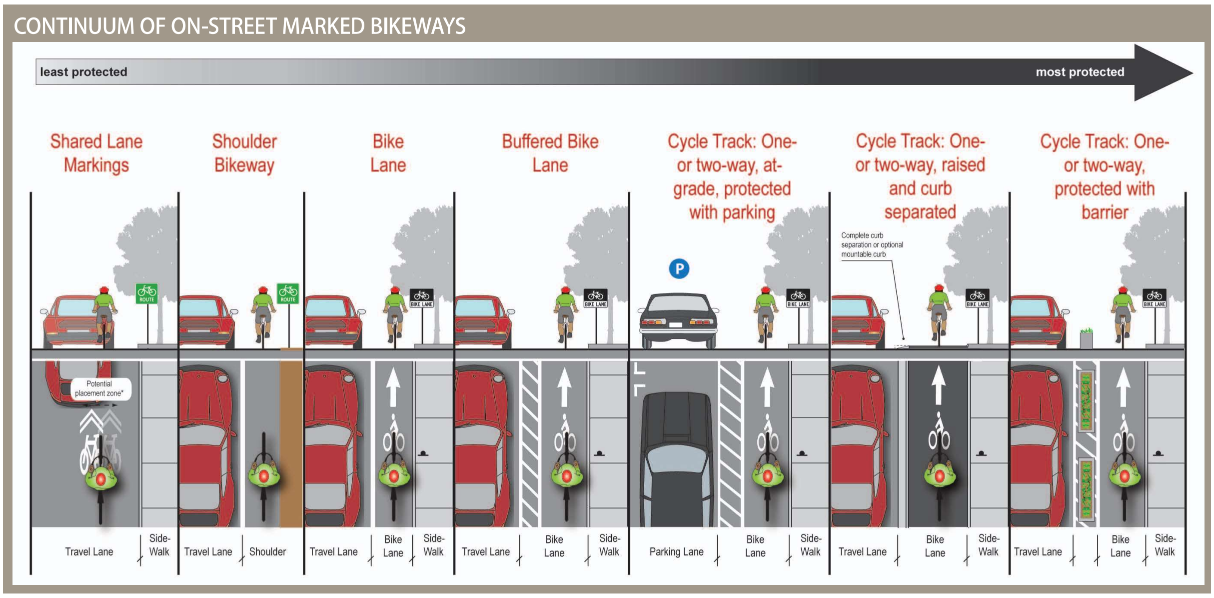

Figure 2. The lane types and its protection to cyclists (Roughton et al., 2012).

$$\hat{y} = \theta_1 x_1 + \theta_2 x_2 + \cdots + \theta_n x_n \qquad (1)$$

Where, x_i indicates the samples of indicator values, θ_i represents the weight of each indicator to be obtained, $\hat{y}$ denotes the ground truth score of each segment. Finally, we compute the scores for each segment to generate a weighted graph model that represents cycling safety.

4. EXPERIMENT RESULTS

4.1 Study area

In our study, we selected the city of Bonn, Germany, as a case for experiment analysis. Bonn is a bike-enjoyable city, making it a great place to explore by cycling (Oehrlein et al., 2018). According to a report published in April 2023 on the official website of Bundesstadt Bonn, Bonn is expanding its bicycle road network by setting up 44 additional lanes covering a distance of 21 km in 2023 and 2024. Once completed, the city will have a 51 km-long bicycle road network. The goal is to improve cycling comfort and safety by closing the gaps in the urban cycling network. Figure 4 shows the location of Bonn.

4.2 Data description

Our main data sources are based on OSM, wherein for the spatial data part, we obtained 127,267 edges and 233,882 nodes using OSMnx[1], which is a Python package to easily download, model, analyze, and visualize street networks and other geospatial features from OSM. We further generated a network graph of the same area, as shown in Figure 5. The indicator data part (e.g., number of lanes, max speed) is mainly extracted from the OSM non-spatial data, stored as key-value pairs, commonly known as tags, associated with spatial objects. These attribute data were normalized and used in the subsequent multi-linear regression analysis.

4.3 Results analysis

As mentioned, Figure 1 shows the safe cycling routes of Bonn, which shows five categories of cycling safety scores, where lower scores indicate safer routes and higher scores indicate less safe routes. In particular, independent lanes indicate legally unrideable routes, but in reality, they are separated from the care lane and are relatively safe in terms of cycling safety. In summary, Most edges have low scores, suggesting Bonn is a city for safe cycling. To support this qualitative analysis, the incorporation of accident statistics will be investigated in order to retrieve possible correlations between our safety score values and the frequency of accidents. Up to now, our safety index includes factors, for instance type lane, issued from OSM data. In order to reflect safety constraints in a more accurate manner, higher resoluted models could be beneficial. Beyond the

[1] https://osmnx.readthedocs.io/

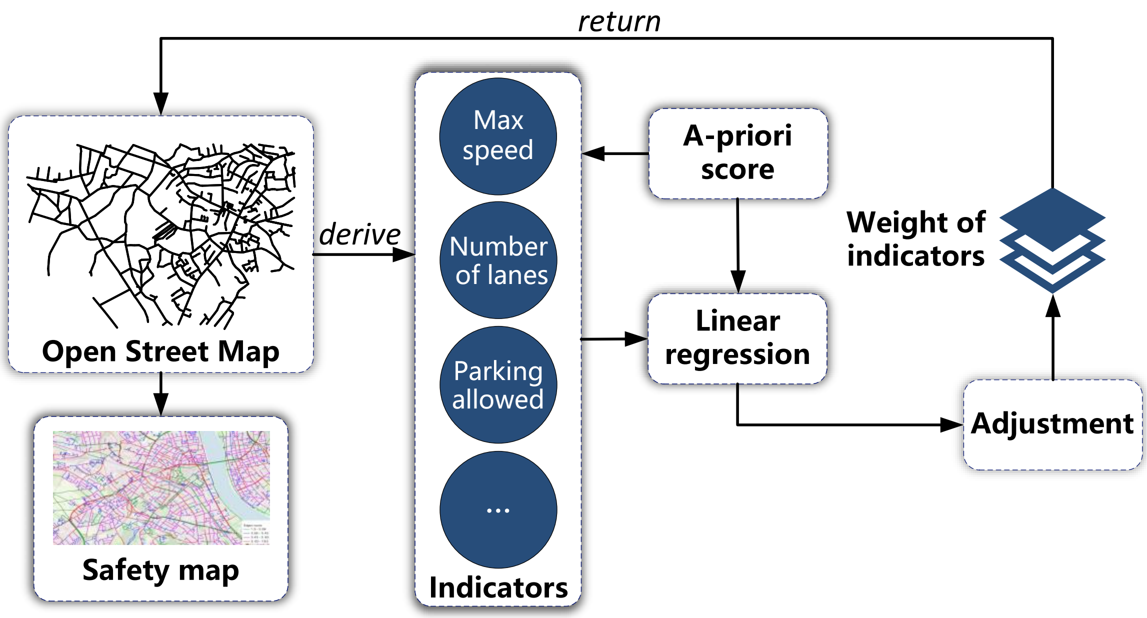

Figure 3. An overview of our method for the safety assessment of cycling routes.

Figure 4. Overview of the research area of Bonn, Germany. Basemap by CartoDB (2024)©.

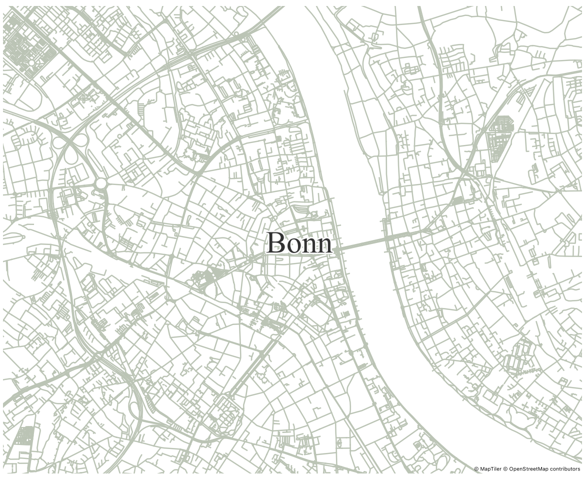

Figure 5. Road network data from OpenStreetMap (2024).

lane type, the width of the underlying lane could be considered based on a high resoluted 3D city model. In this context, the integration of additional factors from a CityGML model (Kolbe et al., 2021) as depicted in Figure 6 is subject of an ongoing work. Vice versa, our safety analysis could be integrated in the 3D city model from Beil et al. (2023) to address more safety aspects such as the bilateral visibility analysis of both cyclists and car drivers within a Driver Digital Twin (DDT). In this context, controlled simulations using, for instance, Simulation of Urban MObility (SUMO) will be used (Amini et al., 2022). Since our approach is independent from the input area, we can develop a qualitative assessment of safe cycling routes to compare different cities. As yet, the ground truth score $\hat{y}$ from equation 1 of each segment of the road network has been assessed from a small sample of questioned users. A work in progress, consists in designing a more elaborated user study based on, for instance, Google Street View. Alternatively, we can retrieve the ground truth scores based on the resulting ranking issued from the participatory system described in Gössling and McRae (2022b).

5. CONCLUSION AND OUTLOOK

The main contribution of our work is the computation of a weighted graph model to identify the safety routes for cyclists automatically. To this aim, a safety index has been proposed taking several factors, e.g. maximal speed and lane types. A multivariate linear regression model has been applied to solve the importance of the considered indicators. The plausibility and feasibility of our method has been evaluated using a qualitative analysis in the city Bonn in Germany.

In the future, one of our main tasks is to perform an in-depth qualitative assessment of our method. For instance, we will integrate the accident statistics to evaluate the correlation between occurred accidents and the safety of the underlying road network, and we will also design a Google Street View-based user study to retrieve the coefficients of the indicators. This will open up new opportunities to integrate the derived safety scores with the edge lengths to address safe routing rather than only

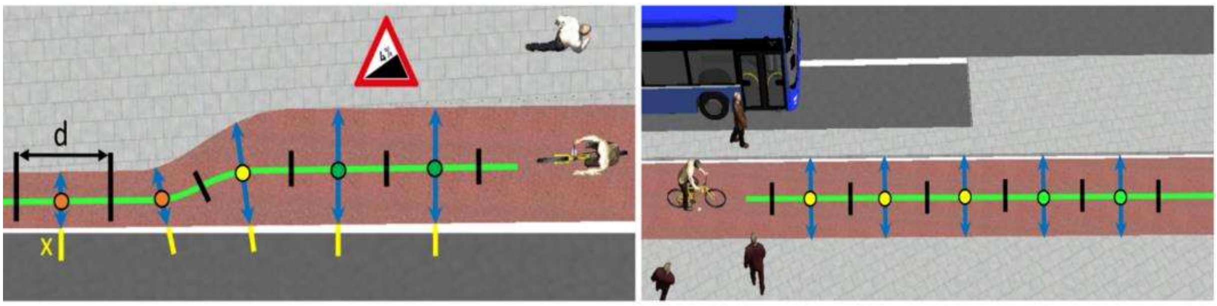

Figure 6. Width calculation of bicycle path (Beil et al., 2023)

shortest path finding. Another aspect to address, is the embedding of our weighted safety graph within a 3D City model including different agents such as cyclists and car drivers. This will allow for taking additional safety factors such as visibility in a controlled simulation environment into account.

6. ACKNOWLEDGEMENTS

The authors would like to express their gratitude to the OpenStreetMap community for their invaluable contribution of open geospatial data.

References

Amini, S., Orlich, C., Beil, C., Keler, A., Bogenberger, K., 2022. Integrating sumo in an urban digital twin - a case study from munich.

Arzoumanidis, L., Forsch, A., Haunert, J.-H., Dehbi, Y., 2023. Catchment cell visualization for multi-modal public transportation networks. *Proceedings of the 1st ACM SIGSPATIAL International Workshop on Sustainable Mobility*, SuMob '23, Association for Computing Machinery, New York, NY, USA, 43–50.

Behrendt, F., 2019. Cycling the Smart and Sustainable City: Analyzing EC Policy Documents on Internet of Things, Mobility and Transport, and Smart Cities. *Sustainability*, 11(3).

Beil, C., Ilic, M., Keler, A., Kolbe, T. H., 2023. Automatically evaluating the service quality of bicycle paths based on semantic 3d city models. *International 3D GeoInfo Conference*, Springer, 75–92.

CartoDB, 2024. Basemaps. carto.com (23 May 2024).

Daraei, S., Pelechrinis, K., Quercia, D., 2021a. A data-driven approach for assessing biking safety in cities. *EPJ Data Science*, 10(1), 11.

Daraei, S., Pelechrinis, K., Quercia, D., 2021b. A data-driven approach for assessing biking safety in cities. *EPJ Data Science*, 10(1), 11.

de Oliveira e Silva, R. A., Cui, G., Rahimi, S. M., Wang, X., 2022. Personalized route recommendation through historical travel behavior analysis. *GeoInformatica*, 26(3), 505-540.

Ding, X., Fan, H., Gong, J., 2021. Towards generating network of bikeways from Mapillary data. *Computers, Environment and Urban Systems*, 88, 101632.

Fan, Z., Yang, X., Yuan, W., Jiang, R., Chen, Q., Song, X., Shibasaki, R., 2022. Online trajectory prediction for metropolitan scale mobility digital twin. *Proceedings of the 30th International Conference on Advances in Geographic Information Systems*, 1–12.

Forsch, A., Dehbi, Y., Niedermann, B., Oehrlein, J., Rottmann, P., Haunert, J.-H., 2021. Multimodal travel-time maps with formally correct and schematic isochrones. *Transactions in GIS*, 25(6), 3233-3256.

Gössling, S., McRae, S., 2022a. Subjectively safe cycling infrastructure: New insights for urban designs. *Journal of Transport Geography*, 101, 103340.

Gössling, S., McRae, S., 2022b. Subjectively safe cycling infrastructure: New insights for urban designs. *Journal of Transport Geography*, 101, 103340.

Huertas, J. A., Palacio, A., Botero, M., Carvajal, G. A., van Laake, T., Higuera-Mendieta, D., Cabrales, S. A., Guzman, L. A., Sarmiento, O. L., Medaglia, A. L., 2020. Level of traffic stress-based classification: a clustering approach for Bogotá, Colombia. *Transportation Research Part D: Transport and Environment*, 85, 102420.

Ito, K., Biljecki, F., 2021. Assessing bikeability with street view imagery and computer vision. *Transportation research part C: emerging technologies*, 132, 103371.

Kolbe, T. H., Kutzner, T., Smyth, C. S., Nagel, C., Roensdorf, C., Heazel, C., 2021. OGC city geography markup language (CityGML) part 1: conceptual model standard. *Open Geospatial Consortium, Wayland, MA, USA*.

Meng, S., Zheng, H., 2023. A personalized bikeability-based cycling route recommendation method with machine learning. *International Journal of Applied Earth Observation and Geoinformation*, 121, 103373.

Mori, K., Christodoulou, A., 2012. Review of sustainability indices and indicators: Towards a new City Sustainability Index (CSI). *Environmental Impact Assessment Review*, 32(1), 94-106.

Oehrlein, J., Förster, A., Schunck, D., Dehbi, Y., Roscher, R., Haunert, J.-H., 2018. Inferring routing preferences of bicyclists from sparse sets of trajectories. *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, 4, 107–114.

OpenStreetMap, 2024. Openstreetmap. openstreetmap.org (23 May 2024).

Panagiotaki, E., Reinmund, T., Liu, B., Mouton, S., Pitt, L., Shanthini, A. S., Towlson, M., Tubby, W., Prahacs, C., De Martini, D. et al., 2024. RobotCycle: Assessing Cycling Safety in Urban Environments. *arXiv preprint arXiv:2403.07789*.

Pucher, J., Buehler, R., 2017. Cycling towards a more sustainable transport future. *Transport reviews*, 37(6), 689–694.

Riccardo Mangiaracina, Alessandro Perego, G. S., Tumino, A., 2017. A comprehensive view of intelligent transport systems for urban smart mobility. *International Journal of Logistics Research and Applications*, 20(1), 39–52.

Roughton, C., van Hengel, D., Duncan, A., Weigand, L., Birk, M., 2012. Creating walkable+ bikeable communities: a user guide to developing pedestrian and bicycle master plans. *Center for Transportation Studies at Portland State University*.

Schepers, P., Hagenzieker, M., Methorst, R., van Wee, B., Wegman, F., 2014. A conceptual framework for road safety and mobility applied to cycling safety. *Accident analysis & prevention*, 62, 331–340.

Schwarz, C., Wang, Z., 2022. The role of digital twins in connected and automated vehicles. *IEEE Intelligent Transportation Systems Magazine*, 14(6), 41–51.

Sun, Q., Feng, T., Kemperman, A., Spahn, A., 2020. Modal shift implications of e-bike use in the Netherlands: Moving towards sustainability? *Transportation Research Part D: Transport and Environment*, 78, 102202.

Szyszkowicz, S. S., 2018. Bikeability as an Indicator of Urban Mobility. *Economic Analysis Directorate Transport Canada Place de Ville, Tower C Ottawa*.

UN, 2022. World cities report 2022: Envisaging the future of cities. unhabitat.org (23 May 2024).

Vito Albino, U. B., Dangelico, R. M., 2015. Smart Cities: Definitions, Dimensions, Performance, and Initiatives. *Journal of Urban Technology*, 22(1), 3–21.

Wang, Z., Gupta, R., Han, K., Wang, H., Ganlath, A., Ammar, N., Tiwari, P., 2022. Mobility digital twin: Concept, architecture, case study, and future challenges. *IEEE Internet of Things Journal*, 9(18), 17452–17467.

Wysling, L., Purves, R. S., 2022. Where to improve cycling infrastructure? Assessing bicycle suitability and bikeability with open data in the city of Paris. *Transportation research interdisciplinary perspectives*, 15, 100648.