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Improving Urban Cyclability and Perceived Bikeability: A Decision Support System for the City of Milan, Italy

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Abstract: This paper presents a Decision Support System (DSS) designed to enhance cyclability and perceived bikeability in urban areas, with an application to the city of Milan, Italy, focusing on cycling toward the urban university campuses of Politecnico di Milano. Despite the increasing emphasis on sustainable urban mobility, research gaps remain in optimizing cycling infrastructure development based on both observable factors (e.g., availability and quality of cycleways) and latent factors (e.g., cyclists' perceived safety and security). The objective of this study is to address these gaps by developing a DSS, based on a macroscopic multimodal transport simulation model, to facilitate an in-depth analysis and prioritization of cycling transport policies. Findings from the DSS simulations indicate that strategic enhancements to cycling infrastructure can shift user preferences toward safer and more dedicated cycling routes, despite potential increases in travel time and distance. This paper concludes that implementing a DSS not only supports more informed policymaking but also encourages sustainable urban development by improving the overall cycling experience in cities, highlighting the importance of addressing both tangible and intangible factors in the design and prioritization of cycling infrastructure projects.

Keywords: urban mobility; cycling; DSS; bike route; path choice

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1. Introduction

Large urban areas often face severe road traffic congestion, which can lead to negative consequences, such as longer commute times, increased pollution, and higher accident rates [1,2]. Therefore, such congestion not only affects the quality of life for residents and city users but also has broader economic and environmental impacts. Nowadays, transport planners and policymakers need access to comprehensive and accurate information about the costs and impacts of congestion in order to enhance the capabilities of transport systems and make informed evaluations about the feasibility of alternative policies and their long-term effects [3,4].

Advanced information technology tools, such as Decision Support Systems (DSSs), enable better decision-making and the development of strategies that address current challenges while anticipating future needs. These systems leverage data and models to assist in analyzing scenarios, predicting outcomes, and optimizing solutions. By providing a structured approach to understanding complex issues, they facilitate effective problem-solving and support decision-makers in identifying the most appropriate actions to take [5–7].

DSSs are employed at various levels within the transport sector [8–11]. Developing a DSS specifically for active transport modes, such as cycling, could be highly beneficial for cities in designing more effective infrastructure and measures to support cycling and other non-motorized forms of transport. Such a system would promote the sustainability of urban mobility environments by encouraging a modal shift from private cars to bicycles for short-distance travel. This shift could help alleviate road congestion [12] and address related issues [13,14].

Although there is growing focus in the literature on sustainable urban mobility, there are still research gaps in optimizing the development of cycling infrastructure by considering both observable factors, such as the availability and quality of cycleways, and latent factors, such as the cyclists' perceived safety and security. This study aims to fill these gaps by developing a DSS based on a macroscopic multimodal transport simulation model, which enables detailed analysis to assess the effectiveness of transport policies and investments in promoting bicycling. The results are demonstrated through an application to the case study of the urban area of Milan, Italy. In particular, the issue of bicycle accessibility to the Politecnico di Milano campuses is addressed, investigating which corridors are most preferred and which infrastructural interventions could improve the perceived bikeability for travelers heading to the university.

The rest of this manuscript is organized as follows. Section 2 provides relevant background concepts for the subsequent sections of this study, including a literature review on three main topics: a taxonomy of DSS for urban mobility, the factors affecting cyclability and perceived bikeability, and the bicycle patch choice models used for transport assignment and simulation. The methodology is described in Section 3 and involves developing a macroscopic simulation model of the transport network of the urban area of Milan and simulating bicycle travel demand toward Politecnico di Milano's university campuses. Section 4 delves into the analysis of an intervention scenario to enhance users' perceived bikeability and discusses the results. Finally, the main conclusions derived from the study are presented in Section 5.

2. Literature Review

DSSs typically consist of three primary components: a comprehensive set of data and knowledge, robust modeling features, and interactive reports and visualizations. The data and knowledge component involves collecting and organizing information from various sources. Data is transformed into knowledge through processes, such as data analysis, pattern recognition, and interpretation. The modeling features use this data and knowledge to simulate scenarios and assess outcomes. By applying models and algorithms, the system uncovers trends and insights that inform decision-making. The interactive reports and visualizations allow users to easily understand and interpret the data, facilitated by user-friendly graphic interfaces.

To better understand the diverse functionalities and applications of DSSs, particularly in the context of urban mobility, a taxonomy of their features is proposed in Table 1 by examining various case studies. This taxonomy is based on several criteria, including the considered modes of transport, the time horizon of decisions, the techniques used to support decision-making, the type of data update connection, the spatial scales of analysis, and the use cases. These criteria allow for differentiation between various aspects of DSS implementations, providing a comprehensive understanding of how these systems function and are utilized in different contexts.

As shown in Table 1, DSSs can involve scheduled transport modes (i.e., public transport services such as buses, trams, subways, and trains), unscheduled (i.e., private vehicles such as cars, mopeds, and e-scooters; shared mobility services such as car-sharing and bike-sharing; and non-scheduled public transport services such as taxis and chauffeurs) or both.

Moreover, DSSs may support different levels and time horizons of decision-making [8]. They can facilitate strategic decision-making, where transport planners and analysts make long-term decisions that define the overall mission and goals of the city administration. Alternatively, they can aid in tactical decision-making, where traffic managers and engineers focus on achieving organizational objectives through mid-term decisions. Furthermore, DSSs can assist in operational decision-making, where supervisors and controllers manage daily tasks, requiring real-time interventions and short-term decisions. Additionally, DSSs can be used in a hybrid decision-making process, allowing the same system to support decisions across multiple timeframes, such as both strategic and tactical levels.

The methodologies employed in DSSs to support decision-making typically fall into two categories:

- Simulation, i.e., a what-if approach, where the impacts and benefits of implementing certain policies or infrastructure projects are evaluated. By simulating different scenarios, it helps to assess how close the outcomes are to the desired targets. This approach allows decision-makers to explore various possibilities and understand the potential consequences of their decisions.
- Optimization, i.e., a what-to approach, where the DSS identifies the policies or infrastructure necessary to achieve a desired target. It focuses on finding the best possible solution to reach specific goals, providing recommendations on the most effective actions to take.

In terms of data update connection, two main types exist. On one hand, offline DSSs operate independently from the physical environment. Users are responsible for manually updating the models' parameters and data over time to maintain their accuracy. On the other hand, online DSSs continuously acquire and update information from the physical environment as it becomes available. This real-time integration allows the DSSs to provide up-to-date insights and decisions based on the latest data, ensuring that the information is always current and relevant [15,16].

Furthermore, DSSs can be applied to different scales of transport analysis. The macroscopic scale of analysis refers to the study of an entire transport network within a city, region, or country. This includes evaluating large-scale systems such as highways, major roads, and overall public transit networks. The microscopic scale involves the most detailed level of analysis, focusing on specific, localized elements of the transport network. This includes examining intersections, squares, bus stops, train stations, and other small-scale infrastructure components. The mesoscopic scale of analysis represents an intermediate level, concentrating on specific subareas, districts, or corridors within a larger transport network.

Finally, DSSs can be utilized in several key fields, each with specific use cases that are described below. For Transport Planning (TP), DSSs assist in identifying optimal locations and sizing for new infrastructure and services, such as roads, bus stops, and docking stations, to enhance the transport network on the basis of demand forecasts. In Traffic Management (TM), DSSs help monitor and optimize traffic flow, manage events and crises such as accidents, enhance safety, and manage congestion. For Fleet Management (FM), DSSs assist in meeting demand efficiently, ensuring that the right number of vehicles are available where needed. In the field of Environmental Impact Assessment (EIA), DSSs evaluate the emissions associated with different transport options and modes, helping to assess and mitigate environmental impacts. Finally, in Revenue Management (RM), DSSs support the development of pricing strategies and tariff schemes, including dynamic road pricing, parking pricing, and yield management.

In general, this literature overview shows that DSSs specifically focused on active transport modes, such as cycling and walking, are underexplored. An exception is the work by Makarova et al. [17], who proposed a DSS for assessing the efficiency and safety of cycling infrastructure projects with a case study in Naberezhnye Chelny, Russia. Although it is not a DSS, another significant attempt to address this research topic is represented by the work of Glavić et al. [18], who developed a decision support framework based on Multi-Criteria Analysis (MCA) methods for cycling investment prioritization. Therefore, this paper aims to provide an additional case study on this topic, focusing on the city of Milan. It offers a different perspective and methodological approach, based on modeling evidence, to contribute to the understanding of the factors that most affect cyclability and perceived bikeability in urban areas and, consequently, identify which investments are a priority for their improvement.

Table 1. Taxonomy of Urban Mobility DSSs.

Study Area [Reference]	Transport Modes	Decision-Making Time Horizon	Methodological Approach	Data Update Connection	Spatial Scale	Use Cases
Thessaloniki, Greece [6]	Unscheduled	Long-term	Optimization, Simulation	Offline	Macro	TP
Milan, Italy [7]	Unscheduled	Long/Mid-term	Simulation	Offline	Meso, Micro	TP, FM
Athens, Greece [10]	Scheduled	Mid/Short-term	Optimization	Online	Macro	TP, FM
Ryazan, Russia [11]	Unscheduled	Mid/Short-term	Simulation	Online	Meso	TM
Athens, Greece [19]	Scheduled, Unscheduled	Long-term	Simulation	Offline	Macro	TP, EIA
Thessaloniki [20]	Unscheduled	Short-term	Optimization	Online	Macro	FM, RM
Amsterdam, Netherlands and Berlin, Germany [21]	Unscheduled	Mid/Short-term	Optimization	Online, Offline	Macro	TP, RM
Naberezhnye Chelny, Russia [22]	Unscheduled	Mid/Short-term	Optimization, Simulation	Online	Macro	TP, EIA
Naberezhnye Chelny, Russia [17]	Unscheduled	Long-term	Optimization, Simulation	Online, Offline	Macro	TP
Singapore and Shangai, China [15]	Unscheduled	Long/Mid-term	Optimization	Online	Meso	TM, FM

For completeness, it is important to clarify that "cyclability" and "bikeability" are terms that are often used interchangeably, but they can have slight differences. On the one hand, the term "cyclability" refers to the ease with which a city or area can be traversed by bicycle. As highlighted by Muñoz et al. [23], Aslam et al. [24], and Ahmed et al. [25], it includes factors such as the presence and quality of bike lanes, the availability of bicycle parking, and other infrastructural and environmental aspects that influence bicycle use. On the other hand, the term "bikeability" is used in a broader context and includes not only infrastructural and environmental aspects (like cyclability) but also the subjective perception of cyclists [26–29]. In other words, bikeability incorporates how cyclists perceive the safety, comfort, and convenience of bicycling in a given area; thus, it is a more holistic measure that takes into account both objective (observable) and subjective (latent) factors [30]. In general, the factors that influence the perceived bikeability (see Figure 1) can be categorized into infrastructure and built environment [31–35], external conditions [36–39], accessibility [40–44], perceived safety, comfort, and social forces [45–50].

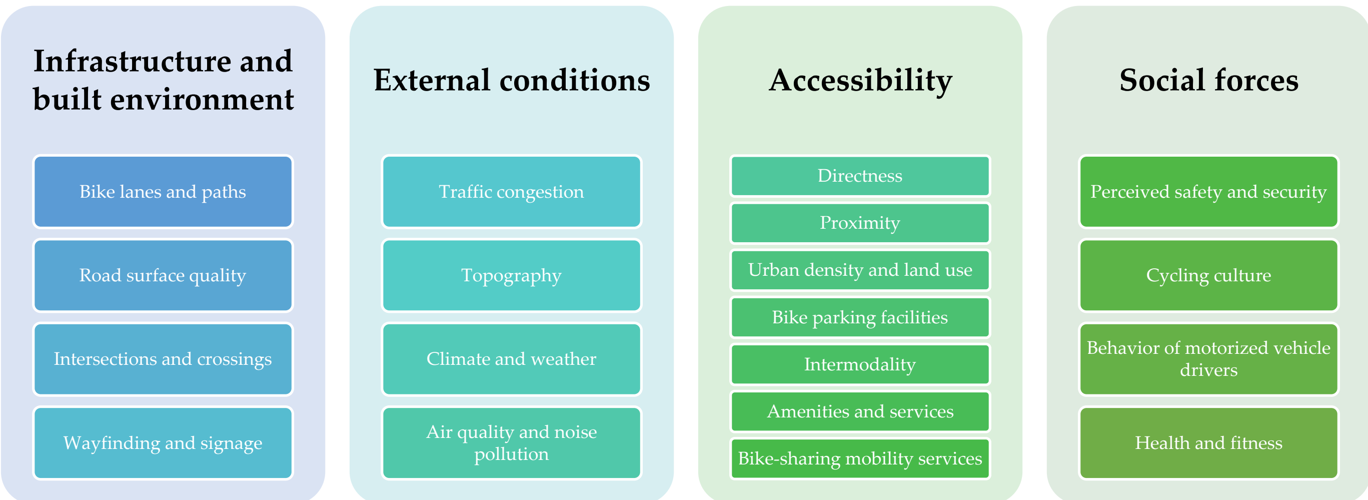


Figure 1. Objective and subjective factors affecting perceived bikeability. Source: authors' own elaboration.

In detail, infrastructure and built environment factors include:

- Bike lanes and paths: i.e., the presence and continuity of dedicated bike lanes and paths. The safest routes are those dedicated exclusively to bicycles, such as bike lanes, followed by paths shared with pedestrians, and, lastly, lanes that are used by both cyclists and motorized vehicles. Cycle paths should be wide enough to allow two bikes to pass or overtake each other safely.
- Road surface quality: i.e., smooth, well-maintained roads and paths without potholes or debris and made from materials that offer minimal resistance, provide good drainage, and are not slippery when it rains.
- Intersections and crossings: i.e., safe, bike-friendly intersections and crossings with appropriate signals and markings. Road visibility must allow for anticipating potential braking and intersections, avoiding sharp right-angle turns. The routes should be free of obstacles like lampposts or benches. Additionally, they should eliminate the need to carry the bike, such as on stairs, by incorporating bicycle ramps where necessary.
- Wayfinding and signage: i.e., clear and comprehensive signage for bike routes and destinations.

External conditions consist of:

- Traffic congestion: high traffic volumes and fast-moving vehicles can make cycling more dangerous and less appealing. Areas with calm, controlled traffic or dedicated bike lanes are more bikeable.
- Topography: i.e., terrain and elevation changes; flatter areas are typically more bikeable. Cycle paths should avoid or minimize slopes and reduce the number of stops, such as traffic lights or intersections, to decrease the need for greater physical effort.
- Climate and weather: mild climates and favorable weather conditions enhance bikeability.
- Air quality and noise pollution: areas with cleaner air are more attractive for cycling. High levels of noise from traffic, construction, or other sources can make cycling less pleasant and deter potential cyclists.

Accessibility factors include:

- Directness: routes between origins and destinations should be as direct as possible, without significant deviations. Cycle paths should run along main streets, which typically host many shops and services.
- Proximity: i.e., easy access to cycling infrastructure from residential and commercial areas. Cycle paths should span the entire city, enabling bicycles to reach as many destinations as possible. Ideally, a cycle path should be within 250 m of any point in the city. They must be continuously connected to each other.
- Urban density and land use: compact, mixed-use urban areas where residences, workplaces, shops, and services are close together encourage cycling. Urban sprawl and car-dependent areas are less conducive to biking.
- Bike parking facilities: i.e., availability and security of bike parking facilities both at the origin and the destination of the routes.
- Intermodality: integration with public transport systems, allowing for easy transition between cycling and other modes of transport, can enhance bikeability. For example, bike racks on buses and trains make multimodal trips easier.
- Amenities and services: i.e., availability of bike repair shops and supportive facilities like showers and lockers.
- Bike-sharing mobility services: availability of public bikeshare systems provides easy access to bicycles without the need for ownership. This makes cycling accessible to more people, including those who cannot afford a bike or prefer not to own one.

Lastly, social factors comprise:

- Perceived safety and security: public perception of road traffic safety and personal security can affect people's willingness to cycle. Areas with lower crime rates and well-lit, secure bike paths encourage more cycling.

- Cycling culture: societal norms and attitudes toward cycling play a crucial role. In cultures where cycling is seen as a normal and respected mode of transport, more people are likely to bike.
- Behavior of motorized vehicle drivers: respectful and cautious behavior from motorists toward cyclists creates a safer environment for cyclists. Drivers who are aware of cyclists and actively look out for them, especially when turning or changing lanes, reduce the risk of accidents. Illegally parked cars and motorcycles or vehicles drifting into bike lanes can endanger cyclists.
- Health and fitness: public awareness of the health benefits of cycling can encourage more people to take up cycling.

These factors have often been investigated using behavioral discrete choice models [51,52]. Specifically, regarding cycling path choice models (also referred to as "bike route choice models"), many studies have demonstrated that it is possible to identify the variables that are statistically significant in influencing the decision of which sequence of cycling arcs (i.e., a cycling path) to take to reach a particular destination and to quantitatively assess the relative weight of these variables. These path choice models have been estimated based on data collected from user samples, sometimes through Revealed Preference (RP) or Stated Preference (SP) survey campaigns and, in other cases, through GPS-tracked trajectories.

For instance, a study by Kang and Fricker [53] focused on identifying the best location for new cycling infrastructure investment in Indiana, USA. They used mixed logit models to analyze the importance of specific characteristics, such as traffic lights, route length, and one-way streets, based on data from intercept surveys. Similarly, Evans-Cowley and Akar [54] conducted a study in Ohio, USA, using visual preference questionnaires from Google Street View to determine which routes were more desirable for cyclists. They evaluated elements like dense canopy, cityscape, parking lots, and pedestrian access using binary logit models. Another research by Caulfield et al. [55] in Dublin, Ireland, used SP questionnaires to identify the preferred types of cycling infrastructure. The analysis included explanatory variables, such as the number of intersections, traffic speed, and dedicated bike lanes, with findings suggesting a strong preference for segregated facilities. Although SP studies are cost-effective and can evaluate hypothetical alternatives, they often suffer from discrepancies between claimed and actual behavior because it is challenging to place respondents in choice situations that accurately reflect their real-world behavior. In contrast, RP surveys, enabled by the advent of geographic information systems (GIS), collect data on actual commuting routes, providing a more accurate analysis of real-world behavior.

Alternatively, many studies have utilized real GPS data collected from cell phones to model path choice preferences. For example, Prato et al. [56] constructed a model for selecting bicycle routes based on value-of-distance, using a large sample of GPS-traced cycling trips in Copenhagen, Denmark. The estimated mixed-generalized logit model considered variables such as amenities, land use characteristics, scenic locations, meteorological conditions, and more. Another study in Amsterdam, Netherland, by Koch and Dugundji [57] employed path choice modeling with GPS data, incorporating factors like noise pollution, land use, distance, and environmental conditions. They compared these variables using three logit models: multinomial, mixed, and mixed path size logit models, finding that cyclists' behavior is highly variable, with a tendency to favor routes with greenery, water, and less traffic over traditional cycleway infrastructure. Additionally, research by Łukawska et al. [58] utilized a large crowdsourced dataset of GPS trajectories in Copenhagen, Denmark, to estimate a joint path size logit model. This model considered various features of the bicycle network, such as surface type, land use, cycling infrastructure type, and major cycle highways. The results indicated that cyclists are significantly deterred by interactions with motorized and non-motorized traffic and are particularly drawn to green and aquatic spaces, especially on longer trips. Finally, Zimmermann et al. [59] proposed a cycling path choice model using GPS data collected in Eugene-Springfield, USA. The estimated link-based recursive logit models highlight that cyclists' path choices are mostly affected by the following factors: distance to be traveled, directness (number of turns), level of congestion on mixed-traffic roads, inclination of the roads, number of left turns, and availability of bike facilities. It is worth highlighting that these factors not only affect the cyclability of an urban area but also influence the cyclists' perceived bikeability. For example, a route that involves crossing intersections with left turns can be objectively more dangerous but also perceived as more (or less) safe than it actually is. This is precisely why cycling path choice models estimated from GPS trajectories undertaken by a sample of cyclists can be more reliable, as they represent cyclists' actual route choices that have been implicitly influenced by both objective and latent factors.

3. Methodological Approach

The methodology adopted in this study to assess the effectiveness of transport policies and prioritize investments aimed at promoting cycling in urban areas involved three main phases, which are schematically represented in Figure 2.

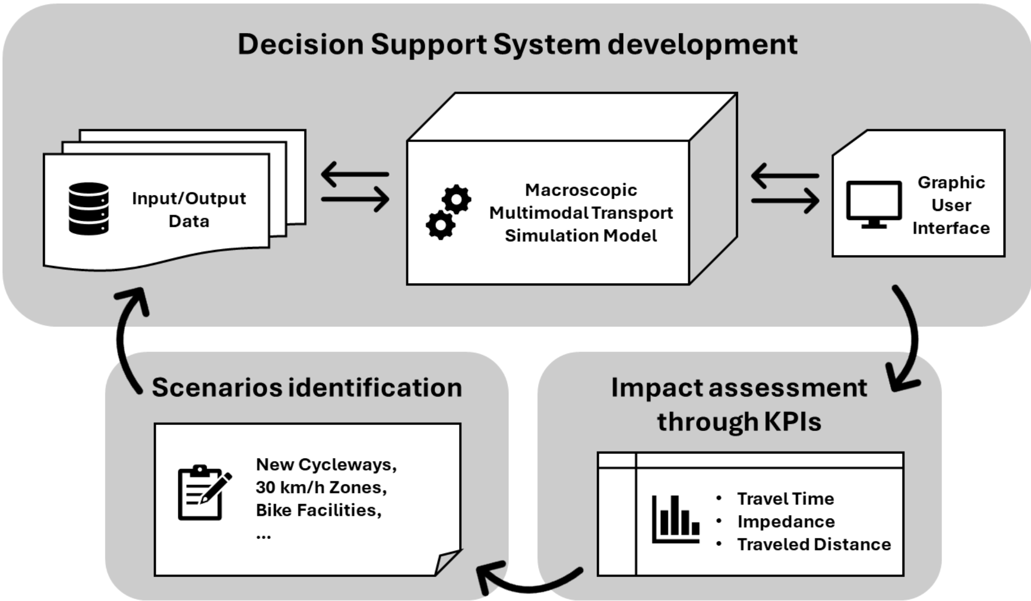


Figure 2. Schematic representation of the methodological approach. Source: authors' own elaboration.

3.1. Decision Support System Development

As a first step, a DSS for the urban area of Milan was developed, with its core being a macroscopic multimodal transport simulation model [60]. The model was built using the simulation software PTV Visum 2024 [61] to take advantage of its powerful Graphical User Interface (GUI) for visualizing simulation input and output data, such as the flows loaded onto the network. The data used to create and validate the model includes both supply and demand information.

Infrastructural data, which consists of transport network elements, such as streets, intersections, and turns, with geometrical and functional characteristics, was sourced from OpenStreetMap (OSM) [62]. Public transport services were imported in General Transit Feed Specification (GTFS) format, containing current scheduled service data operated by ATM S.pA. (Azienda Trasporti Milanesi) from a feed published by AMAT [63] on the open data portal of the Municipality of Milan. The base model includes a graph consisting of 412,833 nodes, 1,070,898 directed links, and more than 600 public transport lines, such as bus, tram, and metro lines. In Figure 3, the cycle network of the inner urban area of Milan is reported, in which the black links represent road segments shared by motorized vehicles, bicycles, and pedestrians. The blue links indicate dedicated cycleways, while the pink links denote footpaths that are also accessible to cyclists. Finally, travel demand data, specifically the Origin-Destination (OD) matrices by transport mode, was imported from open data provided by Regione Lombardia [64].

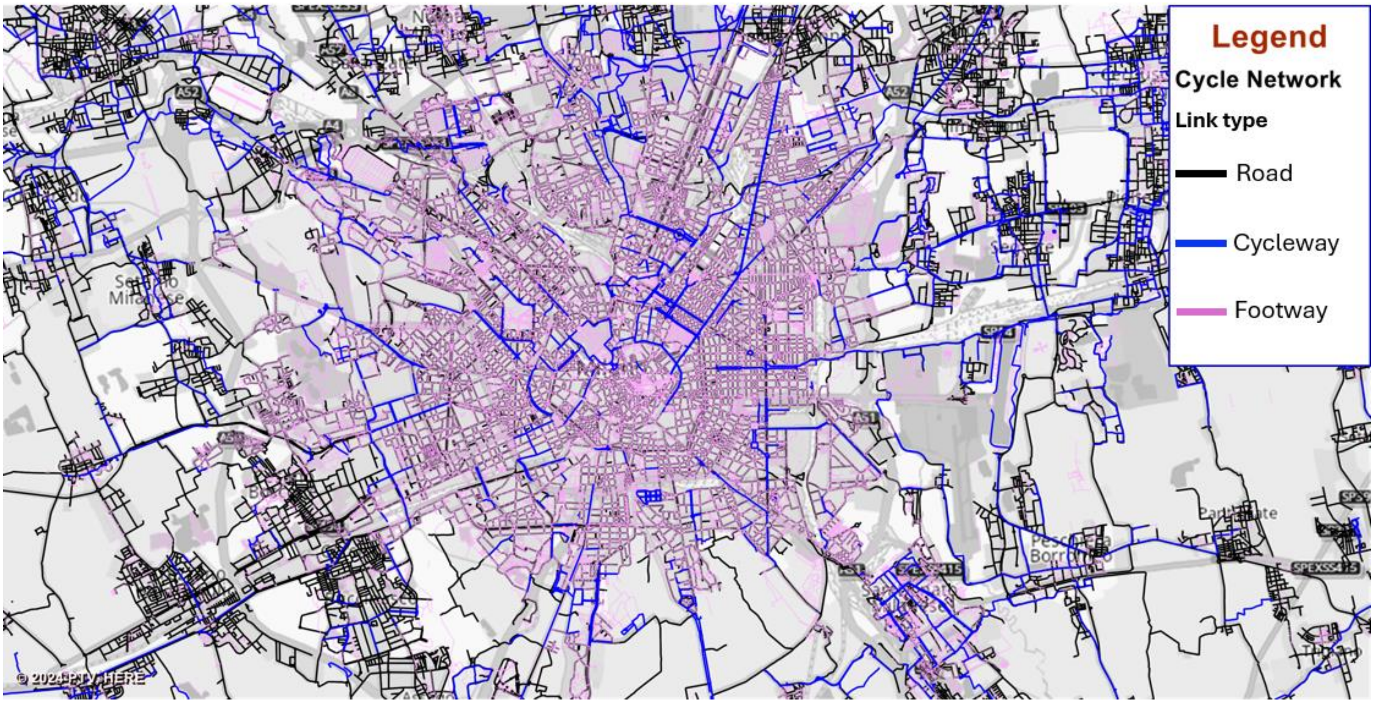


Figure 3. Overview of the cycle network in the inner urban area of Milan, Italy. Source: authors' own elaboration.

Since the cycling path choice model adopted in this research requires traffic flows of cars and mopeds on the road links as input, the multimodal model includes a preliminary traffic assignment procedure for the respective OD matrices before simulating the interactions between supply and demand for cycling. The procedure consists of a Stochastic User Equilibrium (SUE) assignment [65] to account for the impacts of network congestion on travel times. Figure 4 shows the flowchart resulting from the assignment procedure of private motorized vehicles. As can be seen in the innermost part of the urban area of Milan, traffic is concentrated on the characteristic concentric arteries around the historic center, with traffic volumes below 4000 vehicles per hour per direction. The links showing purple and red flow bars (flows exceeding 4000 vehicles per hour per direction) correspond to the highway sections surrounding the city.

Regarding the assignment procedure for bicycle travel demand, the model proposed by Zimmermann et al. [59], previously described in Section 2, has been implemented. This model is, in fact, the most suitable given the similarities between the metropolitan area of Milan and the case study analyzed by the authors, as well as the availability of data in the developed macroscopic multimodal transport simulation model for the city of Milan. Specifically, the cycling path choice model consists of a multinomial logit specification, where the probability of choosing path j is equal to:

$$P(j) = \frac{e^{-V_j}}{\sum_{j'} e^{-Vj'}} \tag{1}$$

where V_j is the systematic utility of path j, expressed as the sum over all the links l that make up the path j of the linear combination of impedance attributes X_{klj} multiplied by the estimated parameters β_k.

$$V_j = \sum_l \sum_k \beta_k X_{klj} \tag{2}$$

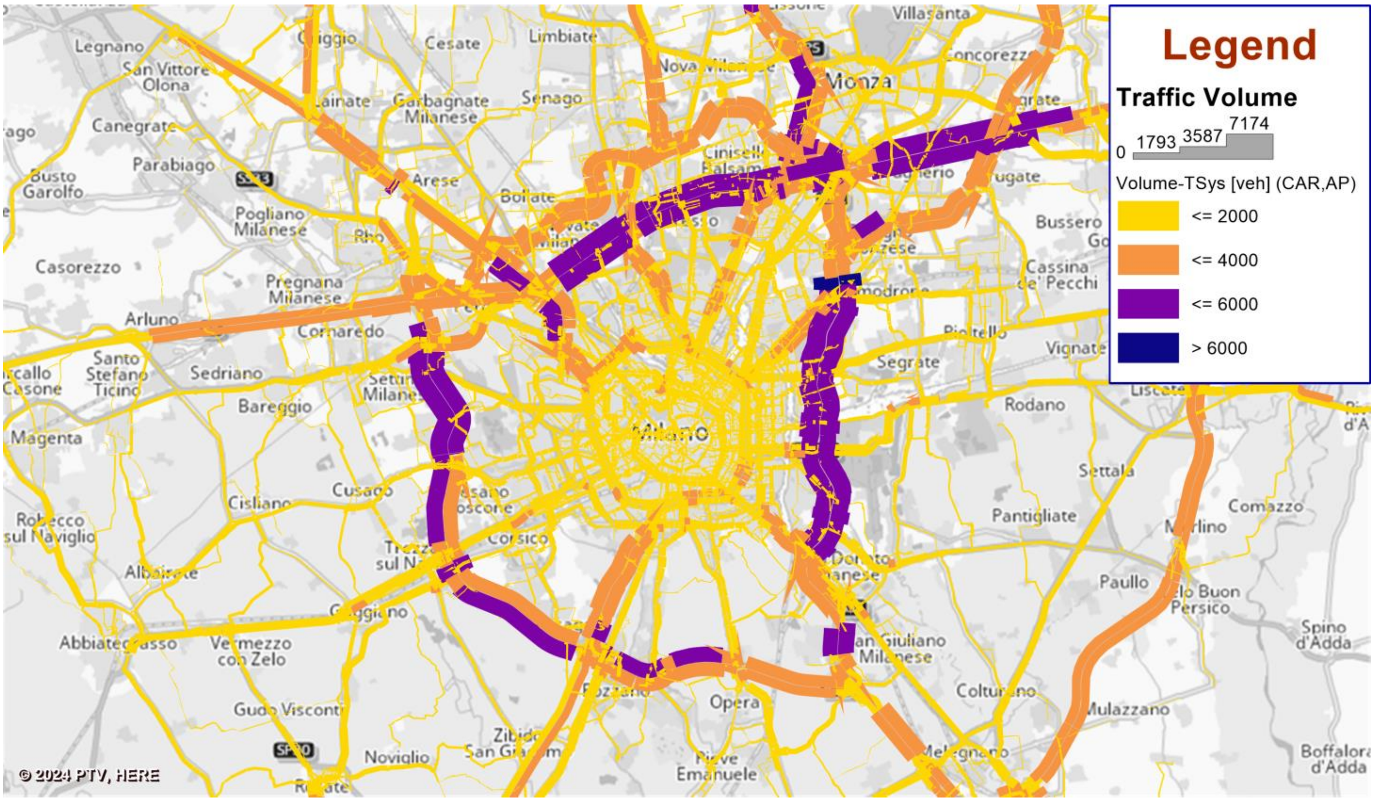


Figure 4. Overview of the traffic volumes of private motorized vehicles. Source: authors' own elaboration.

A description of the considered impedance attributes and the values of the respective estimated parameters β_k is reported in Table 2, along with their levels of statistical significance.

Table 2. Impedance attributes and estimated parameters. Source: Zimmermann et al. [59].

Impedance Attribute X_{klj}	Description	Estimated Parameter β_k	*t*-Test
Length	Link length (1/1000 feet)	−2.25	−17.31
Link Constant	A constant equal to one for each link intended to penalize paths with many crossings	−1.61	−80.50
Length*Upslope	Interaction between link length and average upslope >4%	−3.24	−5.89
Length*Medium Traffic	Interaction between link length and medium traffic volume (between 8000 and 20,000 vehicles/day)	−0.81	−10.13
Length*Heavy Traffic	Interaction between link length and heavy traffic volume (greater than 20,000 vehicles/day)	−1.01	−10.10
Length*Bike Boulevard	Interaction between link length and bike boulevard	0.74	9.25
Length*RMUP	Interaction between link length and regional multi-use path	1.80	25.71
Length*Bike Lane	Interaction between link length and bike lane	0.92	15.33
Bridge	Presence of bridge	−5.41	−5.58
Bridge*Bike Facility	Interaction between the presence of bridge and bike facilities	2.83	5.44
No Turn	Straight direction of travel (no turn ±5°)	1.37	45.67
No Turn*Crossroad	Straight direction of travel at a crossroad	−0.28	−9.33
Left Turn*Crossroad*Medium Traffic	Left turn through medium traffic at crossroad without traffic signal (at an angle between 60° and 179°)	−0.28	3.11
Left Turn*Crossroad*Heavy Traffic	Left turn through heavy traffic at crossroad without traffic signal (at an angle between 60° and 179°)	−1.84	−5.58

3.2. Impact Assessment through Key Performance Indicators (KPIs)

For the evaluation of the benefits and/or costs generated by changes in the transportation supply, some KPIs have been defined ex ante. Specifically, the average travel time spent by each individual for their bike trip and the total distance traveled are considered as summary indicators of the efficiency of the cycling network. Meanwhile, the average impedance of the chosen paths weighted by the associated bike volumes is considered to verify if the measure has contributed to improving the cyclists' perceived bikeability.

In detail, these are obtained as follows:

$$\text{Average Travel Time} = \frac{\sum_j \left(\text{TT}_j \cdot \text{Bvol}_j\right)}{\sum_j \text{Bvol}_j} \tag{3}$$

$$\text{Total Traveled Distance} = \sum_j \left(\text{L}_j \cdot \text{Bvol}_j\right) \tag{4}$$

$$\text{Average Impedance} = \frac{\sum_j \left(\text{V}_j \cdot \text{Bvol}_j\right)}{\sum_j \text{Bvol}_j} \tag{5}$$

where j identifies the path, TT_j is the travel time expressed in minutes, Bvol_j is the volume of bicycles, L_j is the length in kilometers, and V_j is the systematic utility function representing the total impedance of path j.

3.3. Scenarios' Identification

In this paper, the use of the DSS for the urban cyclability and perceived bikeability upgrade is demonstrated with an application to the specific case study of the cycling travel demand of the university community members of the Politecnico di Milano. The population of the Politecnico di Milano, pertaining to the two urban campuses of Milano Città Studi (Leonardo) and Milano Bovisa, consists of approximately 44,000 students and 8000 personnel, including faculty members and technical-administrative staff.

According to the mobility survey conducted for the realization of the Home-Work/University Commute Plan (HWCP) [66], about 3% of the student population in Bovisa travels by bike, while the share of students heading to Leonardo is 5%. This difference is also proportionally observed among the personnel population, where the share of those using bikes for their commuting trips is 6% for those heading to Bovisa and about 11% for those heading to Leonardo. It should be noted that when distinguishing the modal split by distance classes, the modal share of bicycles for trips under 3.5 km is between 14–19% for students and between 15–28% for employees, depending on whether the Bovisa or Leonardo campus is considered, respectively.

In Figure 5, the bicycle flows on the individual network links, and consequently, the preferred paths to reach the urban campuses of the Politecnico di Milano in the current scenario have been mapped. As can be observed, the most significant flows (in green) radiate along four access routes to Leonardo, and there is one major access artery to Bovisa from the eastern side and a minor access route from the western side. These are due to the four-track railway line that divides the latter campus. Additionally, flows from the central areas of the city are clearly visible, along with a significant exchange axis due to those who use bicycles to travel between campuses during the day.

Finally, it is worth noting how, in this current scenario, the network of cycleways (blue links) is highly fragmented, with significant volumes of bicycles forced to use road segments with mixed traffic.

For the sake of brevity, without compromising the demonstration of how the present DSS can be used to identify, through simulation, which policies to prioritize, the results of one intervention scenario are presented and discussed in the next section. This includes infrastructural interventions aimed at interconnecting the currently highly fragmented cycleways network and improving the accessibility of the Leonardo campus.

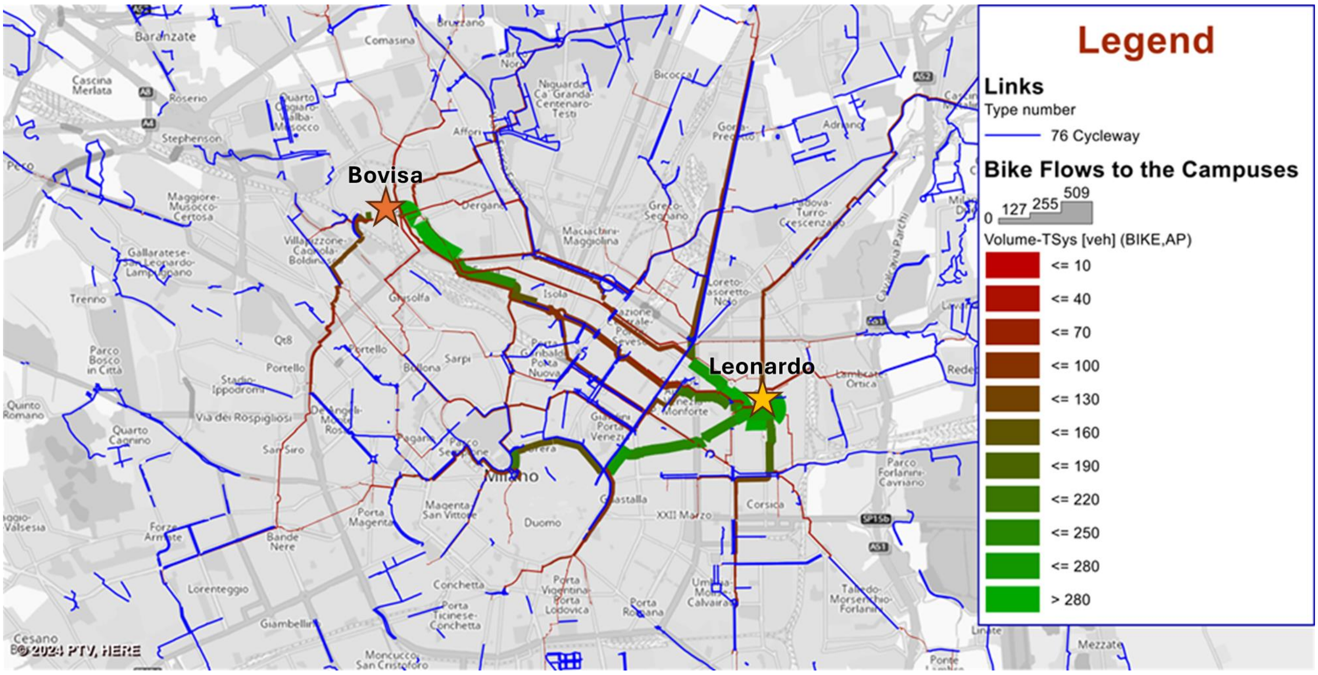


Figure 5. Bike flows accessing the campuses and available cycleways in the current scenario. Source: authors' own elaboration.

4. Results and Discussion

The newly proposed cycleways are represented in Figure 6 with yellow arrows, while the flow bars, graduated from dark red to light green, show the links most preferred for accessing the urban campuses. As can be observed, the implementation of new cycleways has affected the path choice probabilities of each user and, consequently, the overall traffic volumes on the links. Cyclists now would prefer routes that involve greater use of dedicated bike lanes, even if this results in less direct and longer routes.

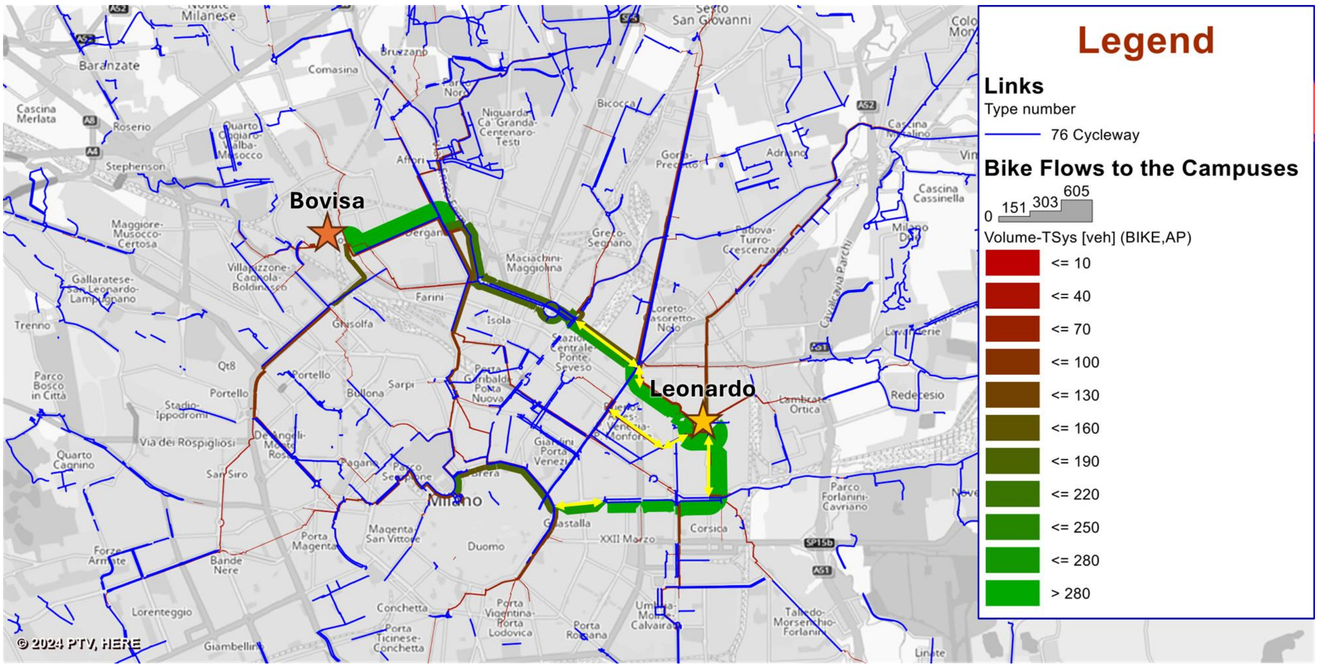
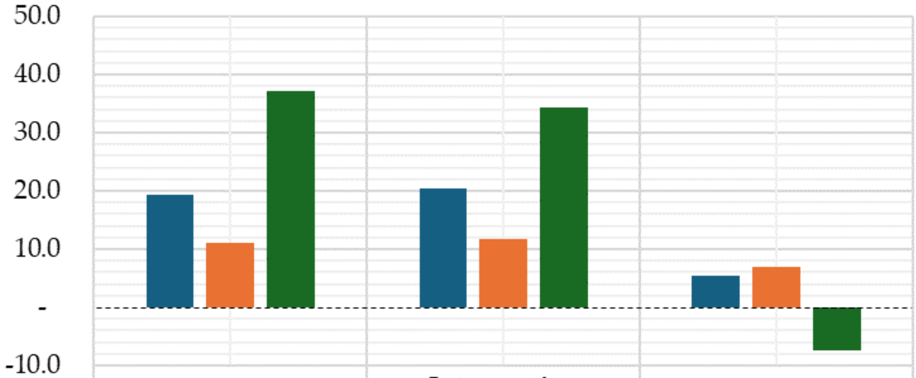


Figure 6. Bike flows accessing the campuses and available cycleways in the intervention scenario. Source: authors' own elaboration.

Regarding the three indicators previously defined in Section 3.2, as shown in Figure 7, the average travel time increases slightly from 19.4 min in the current scenario to 20.5 min in the intervention scenario, reflecting a 5.4% increase. Total traveled distance also shows a modest increase, rising from 11.0 thousand bike-kilometers in the current scenario to 11.8 thousand in the intervention scenario, which represents a 7.0% increase. Conversely, the average impedance decreases from 37.2 in the current scenario to 34.4 in the intervention scenario, corresponding to a 7.4% reduction. These results suggest that although the interventions lead to a modest increase in both travel time and traveled distance, they successfully reduce the average impedance of cyclists. This reduction in impedance indicates an enhancement in the overall perceived bikeability from the cyclists' perspective. In other words, even though the interventions cause longer travel times and greater distances, the decrease in impedance could reflect a more favorable cycling experience, potentially due to factors such as smoother routes, reduced turns, or improved safety, which offset the increased travel time and distance.



	Current Scenario	Intervention Scenario	% Variation
Average Travel Time (minutes)	19.4	20.5	5.4
Total Traveled Distance (thousands of bike-kilometers)	11.0	11.8	7.0
Average Impedance (dimensionless)	37.2	34.4	-7.4

Figure 7. Average results of KPIs. Source: authors' own elaboration.

In regard to the broader findings, this paper makes a significant contribution to the existing literature on urban mobility, specifically in the context of enhancing cyclability and perceived bikeability in urban areas. The primary advancement lies in the development and application of a DSS that integrates simulation tools for assessing and prioritizing cycling policies and infrastructure investments. Previous research has generally focused on evaluating the current state of cycling infrastructure or on the subjective perceptions of bikeability without a robust, quantitative tool that can simulate the effects of potential interventions. This gap in the literature is addressed by offering a systematic approach to visualize and quantify the impacts of specific transport policy interventions, as evidenced by the case study of Milan's cycling environment around the Politecnico di Milano campuses.

Our approach builds on the work of Zimmermann et al. [59], who examined the role of infrastructure quality and safety in influencing cycling behavior. Similar to their findings, our results confirm that perceived safety is a critical factor in route choice. However, unlike Zimmermann et al. [59], who relied on observational data, our study integrates a simulation model that allows for the evaluation of future infrastructure changes and policy interventions.

Additionally, refs. [38,67,68] identified that subjective perceptions of cycling safety, as well as comfort, are crucial in enhancing cycling rates. Our study not only supports this claim but goes further by demonstrating that infrastructure improvements, such as dedicated cycleways and safer intersections, can increase perceived bikeability, even if travel times increase slightly. This finding is consistent with studies like [69,70], which emphasize the importance of comfort and safety over mere efficiency in terms of travel time.

This study extends beyond typical descriptive analyses and provides a methodological framework that could be replicated or adapted in other urban settings. The use of a path choice logit model that incorporates both objective and subjective factors aids in a better understanding of cycling patterns. By doing so, the research not only contributes to a deeper understanding of how various factors, such as route directness, safety, and infrastructure quality, affects cycling preferences but also highlights the importance of considering these factors in urban planning and policymaking.

5. Conclusions

In conclusion, this research contributes to the literature on urban transport planning, particularly in the domain of cycling infrastructure and related policymaking, by providing an in-depth analysis of how DSSs can be applied to enhance cyclability and perceived bikeability in urban settings.

Despite its strengths, the research presents specific limitations that should be acknowledged and addressed in future studies. One significant limitation is the reliance on data from a specific demographic segment, i.e., students and personnel of the Politecnico di Milano, which may not be entirely representative of the wider population of the city of Milan. This could potentially limit the generalizability of the findings. Moreover, the path choice model, while sophisticated, might not fully capture the variability in individual preferences and behaviors, which can be influenced by factors not considered in the model. Future research could overcome these limitations by incorporating a broader demographic dataset and estimating a path choice model to include a wider array of variables, such as weather conditions, economic factors, and individual psychological latent aspects of cycling. Another limitation of the current model is that it does not account for the potential interactions between bicycle and motor traffic or the feedback effects within the transportation network. Future research should aim to incorporate multimodal traffic models that capture these interactions, allowing for a more comprehensive analysis of urban mobility dynamics and the effectiveness of transportation strategies.

From a policy perspective, the findings of this paper suggest that urban and transport planners should consider not only the physical infrastructure but also the perceptual aspects of biking when designing and implementing cycling policies. For instance, the perceived safety and comfort of cyclists on dedicated cycleways can play a significant role in shaping user preferences, as demonstrated by our findings. Even when travel times or distances increase slightly, as shown in our simulations, cyclists tend to favor routes that offer a higher sense of safety, continuity, and separation from motor traffic. This highlights the importance of prioritizing infrastructure quality over pure efficiency in terms of travel time.

Furthermore, the demonstrated increase in perceived bikeability, despite longer travel times and distances, underscores the value of continuous and safe cycleways that encourage cycling, even at the expense of slightly longer commutes. Policies that prioritize protected bike lanes, improved intersections, and traffic-calming measures can mitigate concerns about travel time by enhancing the overall cycling experience. This approach aligns with the broader goal of promoting sustainable urban mobility by focusing on factors that make cycling not only feasible but also appealing and comfortable for a wider range of users. Thus, urban and transport planners should recognize that infrastructure improvements aimed solely at reducing travel time may not be as effective in encouraging cycling as those that enhance perceived bikeability. The results of this study advocate for a holistic approach to cycling policy, where the latent factors of cyclists' behavior are given equal consideration alongside the physical attributes of infrastructure.

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