

Article

Assessing Heterogeneity Among Cyclists Towards Importance of Bicycle Infrastructural Elements in Urban Areas

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Abstract: Promoting bicycling and making it attractive requires appropriate infrastructure. Sociodemographic characteristics, frequency and experiences of bike use, and purpose of bicycle trips can affect preferences towards bicycle infrastructure facilities in urban areas. Hence, this study aims to explore the heterogeneity in the perceived importance of bicycle infrastructure facility attributes in various cyclist groups based on gender, age, weekly biking frequency, daily cycling distance, cycling experience, and bicycle trip purpose. Data were collected from bicycle users through a questionnaire disseminated via social media platforms and QR code brochures distributed in Hasselt, Belgium. A 5-point Likert-type ordinal scale was used to collect data on the perceived importance of bicycle infrastructure facility indicators. The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) was used to rank the indicators. At the same time, Mann–Whitney U and Kruskal–Wallis tests were utilized to verify the heterogeneity among the groups. The findings reveal that bicycle infrastructure, i.e., bicycle lanes or paths, is the most critical variable, while the slope was considered the least important. No heterogeneity was found regarding the importance of bicycle infrastructure indicators based on gender. However, heterogeneity was observed based on age, daily bicycle use, cycling experience, weekly bicycle use, and bicycle trip purpose. The findings of this research help urban and transport planners develop improvement strategies for the city’s existing bicycling facilities and prioritize future developments by considering various cyclist groups’ preferences.

Keywords: bicycle facilities; preference heterogeneity; bicycling; non-parametric test; bicycle infrastructure facilities; TOPSIS



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1. Introduction

Private motorized vehicles consume significant energy to fulfill urban mobility needs [1]. Using fossil fuel-powered transportation is associated with adverse health impacts, including but not limited to climate change, road traffic crashes, lack of physical activity, urban air pollution, and environmental deterioration [2]. Hence, biking has become vital for urban transportation worldwide. The bicycle-friendly environment in urban areas attracts people to using bicycles. Promoting active transport, such as walking and cycling, reduces the use of motorized vehicles and lowers carbon emissions [3,4]. In addition, using bicycles as a mode of transport also has health benefits; for example, it is reported that increasing median daily walking and biking from 4 to 22 min reduced the burden of cardiovascular disease and diabetes by 14% [5]. The problems caused by motorized vehicles have demanded a global push to make cities more amenable to pedestrians and cyclists [6–8]. Cycling is a widely used sustainable means of transportation and is a crucial component of any urban mobility strategy in terms of policy and implementation that aims to enhance urban living standards [9,10].

Promoting cycling and making it attractive requires an appropriate infrastructure [11,12]. For example, bicycles need a secure parking place [13]. Similarly, bicycle signals may be required at junctions for cyclists to cross safely [14]. Road signage increases wayfinding

on cycle paths, improves navigation, reduces stress, and results in shorter travel times for these riders [15]. Also, research suggests that street lighting along bicycle paths is crucial for ensuring that bicyclists feel secure and comfortable [16]. Bicycle facilities at traffic intersections offer cyclists safety, comfort, and convenience [17]. Moreover, the attractiveness of cycling as a viable transport mode depends on the availability of bicycle infrastructure, condition, comfort, and safety [18,19].

Previous studies suggest that bicycle facilities are critical to cycling, as cyclists strongly desire infrastructure that separates cyclists from motor vehicles [20]. Thus, along with being attractive, the bicycle infrastructure must be safe. Also, creating smoother and safer bicycle lanes with clear signage, frequent and high-quality bicycle parking, direct routes, and attractive settings, e.g., greenery, encourages more people to cycle, significantly impacting the environment, traffic congestion, and general health [21,22]. As a result, it is critical to invest in creating bike paths to make riding comfortable, safer, more pleasant, and appealing. The bicycle infrastructure and facilities can be provided in a multitude of ways. For example, a new bike path was installed in inner Sydney, Australia, which resulted in a 23% and 97% increase in bike counts at two locations in 1 year [23]. Another study suggested providing wider bicycle lanes, reducing motorized vehicle speed, increasing visibility at traffic junctions, reducing intersection frequency, and increasing trees along bicycle routes in Brazilian medium-sized cities to promote cycling [24]. European countries like the Netherlands, Denmark, Sweden, and Belgium provide excellent, interconnected bicycle infrastructure to encourage cycling. Additionally, many countries promote using bicycles as feeders for public transportation [25,26].

Studies exploring bicycle infrastructure have employed various metrics, including level of service, bicycle suitability score, and bicycle compatibility index [14]. These metrics evaluate service or bicycle infrastructure performance [3]. A common feature among these methods is their utilization of both objective and, at times, subjective variables to explain perceived infrastructure service or performance. Additionally, there has been a parallel focus on perception studies. One study investigated cyclists' perceptions to inform successful bicycle promotion strategies, emphasizing psychosocial factors such as efficiency, flexibility, fun, danger, and vandalism [27]. Another investigation explored the impact of individual perceptions on potential bicycle infrastructure improvements, policies, and programs within a campus setting [28]. This research developed a framework to identify factors influencing the decision to bike. Furthermore, a recent study concentrated on the social benefits of bicycle-friendly infrastructure, considering infrastructural variables like route visibility, road surface quality, segregation from motorized vehicles, and integration with public transport [1].

Existing studies have explored cyclists' perceptions for investigating factors such as psychosocial elements, individual perspectives on potential infrastructure improvements, decision-making factors influencing biking, and the social benefits of bicycle-friendly infrastructure. There is a noticeable research gap concerning investigating cyclists' perceptions of bicycle infrastructural indicators based on sociodemographic and cycling activities, i.e., cycling experience and frequency. Moreover, those studies have ignored the heterogeneity of bicycle infrastructure indicators in various groups. Hence, this research aims to investigate the heterogeneity among cyclists in the critical elements of bicycle infrastructure. Understanding different cyclist groups' perceptions based on gender, age, and cycling frequency and experience will help understand diverse needs, which is crucial for better informing urban planners and policymakers. The insights gained from this research will guide urban and transport planners in prioritizing investments in bicycle infrastructure, addressing cyclists' specific concerns and preferences to create a more inclusive bicycling environment.

The remainder of the paper is structured as follows. Section 2 reviews the relevant literature on user perception-based studies and attributes influencing cycling infrastructural facilities. Section 3 describes the rationale behind using non-parametric statistical tests and the TOPSIS method used in the study. It also describes the study area, sample size, and questionnaire for data collection. Section 4 presents the study's results, while Section 5

critically discusses the study's findings. Lastly, Section 6 presents the study's conclusions, limitations, and the future scope of the work.

2. Literature Review

Previous research has covered a range of characteristics that could affect how often people bike. For example, attitudes and perceptions affect individuals' intention to use the bicycle as the primary mode of transportation [25]. One crucial aspect for bicyclists is road safety, as the frequency of accidents involving cyclists and motorized vehicles is often assessed across various types of infrastructure [29,30]. Cycling infrastructure along urban street segments positively influences the perceptions of cyclists' safety [18,31]. Also, their subjective road safety assessment influences the frequency of cycling and the routes chosen by cyclists [32]. When designed with safety in mind, these infrastructures reduce the likelihood of road traffic accidents and injuries involving cyclists. For example, improving cycling infrastructure to reduce situations where bikes leave the carriageway, such as dedicated cycling paths, is crucial in preventing accidents and improving overall safety [33]. Also, cycle tracks, which physically separate cyclists from motorized traffic, have shown a reduction in crash rates [34]. However, their effectiveness varies depending on specific design elements, such as being one-way or two-way. Also, cyclists experience lower physiological stress (measured by heart rate variability and galvanic skin responses) when riding in dedicated bike lanes compared to no-bike lane conditions [35]. This suggests that the quality and safety of infrastructure directly impact cyclists' physical and psychological well-being.

Facilitating environments is well recognized in the literature as a relevant dimension to explain travel behavior [36]. For example, facilities explicitly designed for bicycles, such as designated bike lanes and paths, are effective measures to attract more people to cycling [3]. In addition, it also lowers cyclists' collisions and injuries [37]. The effects of users' attitudes and perceptions about the characteristics of the cycling environment have been associated with how commuters perceive and evaluate cycling risks and benefits [38]. Socioeconomic characteristics and familiarity with bicycles usually have a direct impact on bicycle choice decisions [36]. In addition, bicycle infrastructure contributes to the explanation of bicycle choice.

Previous research on cycling has also investigated the significance of attitude in explaining bicycle use or engaging in cycling activities. Some studies have described cognitive and affective components as distinct influencers [39,40]. Others have amalgamated them into a single explanatory factor [27,41]. For instance, employing structural equation modeling, it was validated that attitude, construed as a latent construct encompassing both affective and cognitive elements (such as "I enjoy cycling," "I prefer cycling over driving whenever feasible," and "Cycling can sometimes be more convenient than driving"), plays a pivotal role in understanding cycling behavior [41,42].

The bicycle infrastructure must be designed for the comfort of cyclists along with safety concerns. For example, perceptions of comfort were used to inform recommended bike lane buffer types [18,43]. Similarly, research was conducted on cyclists and residents of neighborhoods adjacent to newly implemented protected bike lanes in five cities across the United States [44]. The protected bicycle lanes were evaluated using video recordings, bicycle count data, bicyclist intercept surveys, and surveys from nearby residents. The results suggested that 10% of current cyclists transitioned from other modes of transport, while 24% moved from different bicycle routes. In addition, more than 25% of cyclists reported that they are biking more frequently overall because of the protected bike lanes. One study on cycling infrastructure (in 90 major U.S. cities) demonstrates that cities with more bike paths and lanes have higher rates of bike commuting. Another study utilized comfort ratings from video clips to evaluate the appropriateness of various intersection treatments linked with separated bike lanes [45]. Similarly, cyclists' comfort ratings from video clips were employed to establish a level-of-service rating for protected bike lanes based on buffer types, motor vehicle volumes, and speeds [46].

Several studies have found that attitudes and perceptions affect individuals' intention to use the bicycle as the primary mode of transportation [27,47]. One study found that perception factors, such as proximity and convenience of the location, affect the choice of bike-sharing systems [48]. Another study accounted for perceptions and attitudes on bicycle access [49]. Moreover, in a study about travel behavior, there was a positive perception of specific product attributes that influenced product usage only if coupled with two attitudinal variables: beliefs and affect [50]. However, attitude and perception and their relative importance in predicting the importance of bicycle infrastructural elements are expected to vary across different socio-economic groups and bicycling usage.

Recent technological advancements have also contributed to understanding user behavior and infrastructure preferences. Internet of Things (IoT) monitoring systems offer a crucial understanding of users' preferences and behaviors. For instance, IoT sensors installed on bicycles and infrastructure can track movements, usage patterns, and interactions, producing meaningful data that can guide the improvement of design and planning [51]. Also, Floating Car Data offers information such as origin and destination path features. This information helps identify the trips that can be substituted with sustainable modes [52]. However, it is also important to note that perception of the infrastructure elements is key in planning new facilities or improving the existing facilities.

In conclusion, the literature highlights the influences on cycling behavior, ranging from individual attitudes and perceptions to environmental and infrastructural factors. Studies have consistently highlighted the significance of perceptions in determining individuals' intentions to use bicycles as their primary mode of transportation, with various factors such as bicycle infrastructure elements and socioeconomic characteristics playing crucial roles. Safety, comfort, and attractiveness are not just optional features of cycling infrastructure but fundamental requirements for promoting bicycling. To improve these features of the bicycling environment, it is crucial to prioritize the design of infrastructure that meets cyclists' needs. Furthermore, despite the generally positive impacts of infrastructure, the effectiveness of treatments such as bike lanes and cycle tracks can vary significantly depending on their design and implementation [34]. This highlights the need for context-specific planning and evaluation. Moreover, by assessing cyclists' perceptions and addressing their concerns about bicycle infrastructure, relevant improvement and prioritization can be made, making cycling a sustainable, healthy, and accessible transportation option. Nonetheless, a noticeable gap remains in exploring the heterogeneity in cyclists' perceptions of bicycle infrastructural elements. Existing research has overlooked how perceptions vary among different demographic and cycling groups. This study addresses these gaps by assessing how age, gender, daily cycling use, weekly cycling use, and cycling experience influence cyclists' perceptions of various bicycle infrastructure elements.

3. Materials and Methods

This section focuses on the rationale behind the chosen non-parametric methods and the TOPSIS. Two non-parametric methods have been utilized: the Mann–Whitney U and Kruskal–Wallis tests.

3.1. Non-Parametric Tests

The cyclist perceived importance ratings were gathered on a 5-point Likert scale; '1' represents the least importance, and a scale of '5' shows that the attribute is the most important. The data type is ordinal, as the variables are ranked from highest to lowest. Unlike continuous or interval data, whose central tendency may be determined by the mean value, ordinal data are intended to have their central tendency quantified by the median value [53]. Hence, reporting the mean or standard deviation of ordinal data is inappropriate, implying that statistical techniques like the *t*-test, F-test, and ANOVA, commonly used parametric methods, are not suitable and inappropriate [54–56].

Several non-parametric tests, such as the Mann–Whitney U test, Wilcoxon W test, Kruskal–Wallis H test, etc., can be used to examine differences and patterns in data collected

using Likert scales or similar ordinal measures. However, the criteria for these non-parametric tests vary depending on their application in analyzing ordinal rating data [57]. Two non-parametric tests are particularly relevant when comparing two groups based on a categorical independent variable: the Wilcoxon test and the Mann–Whitney U test. [58]. The Kruskal–Wallis H test, a well-known non-parametric test based on ranks, is an alternative to the one-way ANOVA for comparing multiple groups [53]. Hence, this study utilizes the Mann–Whitney U and Kruskal–Wallis H tests to verify the preferred heterogeneity in bicycle infrastructure variables among different cyclist groups. The Mann–Whitney U test is used for two independent groups, i.e., male and female; the Kruskal–Wallis H test is appropriate for comparing more than two groups.

3.2. TOPSIS Method

TOPSIS is a well-known multicriteria decision-making method (MCDM) widely used in transportation to prioritize facilities [56,59,60]. Other MCDM methods exist, such as the Analytical Hierarchy Process, Elimination and Choice Expressing Reality. However, the TOPSIS method is simple and yields an unquestionable preference classification [61].

The following procedure adopted for the analysis was previously used in similar research, i.e., for investigating commuters' perception of the metro transfer facility attributes [62]. Similarly, it has been utilized to evaluate the location of existing park-and-ride facility attributes [60].

Step 1: A decision matrix ($m \times n$) consisting of bicycle facility ranks (1–5) in the column and bicycle infrastructure variables (alternatives) in the rows was formulated. The matrix structure is represented using Equation (1) as below.

$$x_{ij} = \begin{bmatrix} x_{11} & x_{12} & x_{13} & \cdots & x_{1n} \\ x_{21} & x_{22} & x_{23} & \cdots & x_{2n} \\ x_{31} & x_{32} & x_{33} & \cdots & x_{3n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & x_{m3} & \cdots & x_{mn} \end{bmatrix} \quad (1)$$

where x_{ij} is the decision matrix, i ranges from 1 to m , representing each alternative (bicycle infrastructure elements), and j ranges from 1 to n , n representing each criterion (rank: 1, 2, 3, 4, 5).

Step 2: Calculate the normalized decision matrix (r_{ij}) using Equation (2).

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^m x_{ij}^2}} \quad i = 1, 2 \dots m, j = 1, 2 \dots n \quad (2)$$

where r_{ij} represents the normalized value of the element x_{ij} in the normalized decision matrix.

Step 3: Calculate the weighted normalized decision matrix (t_{ij}) using Equation (3). This is calculated by multiplying each element in the normalized decision matrix by its corresponding criterion weight.

$$t_{ij} = r_{ij} \times w_j \quad i = 1, 2 \dots m, j = 1, 2 \dots n \quad (3)$$

where w_j represents the weights. The weighting of the five rating levels (criteria) in Step 3 was considered carefully, and equal weights ($w_j = \frac{1}{n}$) were given to all levels. The approach is based on the principle of equal probability, where each rating level (1 to 5) has an equal opportunity of being selected when presented to the respondents (cyclists in this study) to express their perception of the importance of bicycle infrastructure elements. Also, equal weighting avoids bias towards any rating level, allowing for a more neutral assessment of respondent preferences. In addition, from the respondent's perspective, each rating level is an equally valid option for expressing their opinion.

Step 4: Calculate the ideal best (J^+) and the ideal worst (J^-) solutions using Equations (4) and (5).

$$J_j^+ = \begin{cases} \max(t_{ij}) & \text{for positive criteria} \\ \min(t_{ij}) & \text{for negative criteria} \end{cases} \quad (4)$$

$$J_j^- = \begin{cases} \min(t_{ij}) & \text{for positive criteria} \\ \max(t_{ij}) & \text{for negative criteria} \end{cases} \quad (5)$$

Step 5: Calculate the Euclidean distance for each alternative to the ideal best (d_j^b) and the ideal worst solution (d_j^w) using Equations (6) and (7).

$$d_j^b = \sqrt{\sum_{i=1}^n (t_{ij} - J_j^+)^2} \quad i = 1, 2, \dots, m, \quad j = 1, 2, \dots, n \quad (6)$$

$$d_j^w = \sqrt{\sum_{i=1}^n (t_{ij} - J_j^-)^2} \quad i = 1, 2, \dots, m, \quad j = 1, 2, \dots, n \quad (7)$$

where d_j^b is the distance from the ideal best and d_j^w is the distance from the ideal worst solution.

Step 6: Determine the TOPSIS score (S_i) of the alternative using Equation (8). The S_i values indicate the performance of each alternative (bicycle infrastructure elements), allowing attributes to be ranked according to their proximity to the ideal solution.

$$S_i = \frac{d_j^w}{d_j^w + d_j^b} \quad (8)$$

Step 7: Rank the bicycle infrastructure indicators based on the S_i ($i = 1, 2, \dots, m$). The S_i value is between 0–1; a value closer to 1 indicates that the variable is more important, while a value near 0 shows that the variable is less important.

3.3. Study Area

The research was done in the city of Hasselt, Belgium. Figure 1 shows the map of Hasselt. Hasselt is a small city with a population of 80,846, but it has a well-established bicycle infrastructure. Hence, it offers a manageable environment for studying cyclists' perceptions of bicycle infrastructure. Its relatively small size ensures that data collection and analysis can be performed more precisely, allowing for a detailed examination of cyclists' diverse experiences.

Additionally, the city's well-developed and varied bicycle infrastructure, comprising different bike lanes, pavement materials, and bicycle prioritization measures, provides a comprehensive basis for assessing how these factors influence cyclists' perceived importance of various infrastructural elements. By exploring this diverse infrastructure, the study aims to see which elements are most valued by cyclists and how these preferences vary across different groups.

The city of Hasselt is well known for having excellent bicycle infrastructure, which highlights the city's commitment to sustainable urban life. The city demonstrates its commitment to promoting eco-friendly and efficient means of transportation with its outstanding network of well-maintained bike lanes, parking zones, and programs like bike-sharing. Figure 2 shows some examples of the condition of the existing bicycle infrastructure in the city: (2a) a bicycle-prioritized street (paved with red color), (2b) separate bicycle traffic signals at a junction, (2c) a shared (with pedestrians) bicycle lane separated from motorized traffic through trees, (2d) a bicycle lane separated from a motorized traffic lane by a median. To attract and retain more cyclists, it is essential to understand which bicycle infrastructure indicators are most important. For the mentioned purpose, the attributes should be investigated based on their perceived importance to cyclists, helping policymakers prioritize cycling infrastructure.

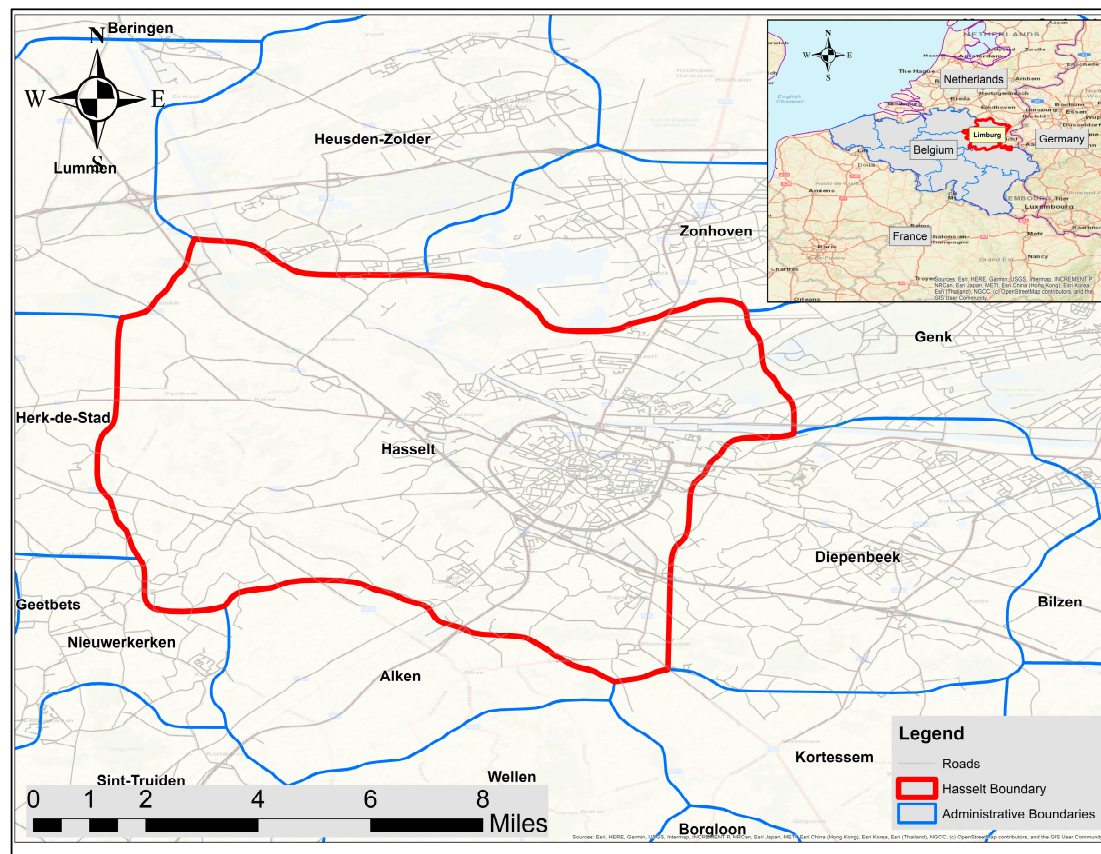


Figure 1. Study area map.



Figure 2. Examples of bicycle infrastructure facilities in Hasselt. (a) bicycle-prioritized street paved in red, (b) separate bicycle traffic signals at a junction, (c) shared bicycle lane with pedestrians, separated from motorized traffic by trees, (d) bicycle lane separated from motorized traffic by a median.

3.4. Selection of Bicycle Infrastructure Variables

A comprehensive literature review of research articles and bicycle infrastructure design guidelines was done to shortlist the indicators using three academic databases, i.e., Web of Science, Scopus, and Google Scholar. After a comprehensive review, 14 bicycle infrastructure facility indicators were selected. Table 1 shows the selected indicators for this study.

Table 1. Selected indicators for the study.

Indicators	Notation	References
Presence of bicycle lanes, paths	PBI	[9,63–67]
Pavement type	PT	[65,68–70]
Bicycle lane width	LW	[65,68,69,71]
Sidewalks width	SW	[65,72,73]
Grade	GR	[9,65,68,74]
Motorized traffic speed	TS	[68,75]
Traffic control devices	CD	[68,69,76–78]
Street lighting	ST	[65,66,79]
Car parking along the cycle path	CP	[64,65,80]
Availability of bicycle parking	ABP	[63,80]
Trees/green area and landscaping	TRL	[64,71,74,78,79,81]
Bicycle facilities at traffic signals	CYJ	[66,75,80,82]
Road signage	RS	[64]
Interruptions	ITR	[65,67,80]

The independence of the criteria used in this study is supported by their selection through a comprehensive literature review, ensuring that each represents a distinct aspect of bicycle infrastructure. Also, during the questionnaire design, care was taken to present each indicator as a separate factor for evaluation.

3.5. Questionnaire

The survey instrument, available in English and Dutch, employed a Likert-type ordinal scale ranging from 1 to 5 [83]. The questionnaire had two main sections to gather information: (i) the sociodemographic and riding characteristics of cyclists and (ii) their perceived importance of various attributes related to bicycle infrastructure indicators. The survey was conducted online because it is efficient and time-saving. The first section of the questionnaire explored sociodemographic information, covering factors such as age, gender, cycling preferences, and the frequency of cycling trips of the participants. In the subsequent section, cyclists rated the perceived importance of bicycle infrastructure facility attributes using a Likert scale ranging from 1 to 5, where ‘1’ indicated not important and ‘5’ indicated very important.

3.6. Sample Size

We employed the Krejcie and Morgan formula to determine a sample size for this research. Equation (9) shows the Krejcie and Morgan sample size formula.

$$n = \frac{X^2 N p(1 - p)}{e^2(N - 1) + X^2 p(1 - p)} \quad (9)$$

where n is the required sample size for the study, Np is the population size, e is the sampling error, X^2 = chi-square with a degree of freedom 1 and confidence level 95%, and p is the

proportion of the population (if unknown, 0.5). The sample size for the city of Hasselt (population 80,846) with a 95% confidence level and a 5% margin of error is 383 individuals. The 95% confidence level corresponds to a Z-score of 1.96, and an estimate of the population proportion ($p = 0.5$) is assumed to account for maximum variability. This methodological approach in selecting sample size ensures that the selected sample is representative of the larger population, laying a robust foundation for meaningful statistical inferences in subsequent analyses.

3.7. Data Collection

The questionnaire was drafted using the Qualtrics platform [84]. Qualtrics provides a user-friendly interface for the respondents, facilitating an excellent survey-taking experience that enhances overall participant engagement and data accuracy. Before the data collection, the survey was distributed among seven experts (three practitioners from the town hall of Hasselt and four active researchers) to identify any mistakes in the drafted survey. In addition, they were also asked to identify any difficulty in understanding the questionnaire in terms of technicality and language. After the pilot survey, the final questionnaire underwent necessary modifications to address the identified issues. The wording used to describe the survey features and variables was mainly changed to improve comprehension and clarity.

A multifaceted distribution strategy was employed to ensure a diverse and representative sample for our survey. The survey link and QR code were generated from the Qualtrics platform. The questionnaire link was extensively disseminated online through various social media platforms, such as Facebook and Twitter, taking advantage of the broad reach and accessibility of digital platforms. The link to the survey was also shared with the cycling community in Hasselt. The link was distributed in both Dutch and English. A QR code facilitating quick and convenient access was distributed across social media and printed on the brochures. Questionnaire brochures were distributed in areas like the city center, cafes, bicycle repair shops, and important locations, including busy bus stops and the train station.

Furthermore, the brochures were also distributed in educational institutions, such as university campuses, colleges, schools, and libraries. Employing a diverse distribution strategy, we aimed to capture a broad category of respondents, ensuring inclusivity and increasing the likelihood of obtaining a representative sample for our research. Of 383 responses, 277 were recorded via a shared link, while the remaining 106 were recorded using QR. Regarding the choice of language, 217 (56.7%) respondents chose Dutch, while the remaining 166 (43.3%) completed the questionnaire in English.

3.8. Reliability Assessment of the Questionnaire Results

The Cronbach's alpha test was conducted to determine whether the questionnaire responses could be relied on. The Cronbach's alpha value was determined using Equation (10).

$$\alpha = \frac{K}{K-1} \left(1 - \frac{\sum_{i=1}^k \sigma_{y_i}^2}{\sigma_x^2} \right) \quad (10)$$

where k represents the number of items in the test, $\sigma_{y_i}^2$ is the variance of the scores on items i , and σ_x^2 is the variance of the observed test scores.

The reliability test included all the items, and Cronbach's Alpha coefficient value was 0.815. Including all items in the reliability test aligns with our aim to evaluate the bicycle infrastructure attributes by considering all the relevant indicators. A Cronbach's alpha value exceeding 0.8 suggests good consistency, indicating that the survey responses are dependable and can be relied on [85]. Also, a high level of reliability implies that the study's findings are likely to be robust, providing confidence for the formulated conclusions.

4. Results

4.1. Sociodemographic Characteristic

Table 2 shows the sociodemographic characteristics of the respondents. In Table 2, the percentage in parentheses indicates the proportion within gender, and the percentage in the last column (also in parentheses) shows the total percentage for each category. Respondents' genders were relatively balanced, with 50.4% male and 48.3% female. Five participants did not disclose their gender. Most respondents (35.8%) were in the 18–24 age group, followed by the 35–44 age group (32.1%). Only two respondents were older than 65, and the category 55–64 years also had minimal representation, with only eleven respondents. The participants' educational backgrounds were diverse, with the majority holding Master's (36.6%) and bachelor's degrees (29.2%). Based on the survey, student respondents comprised the majority (57.4%), indicating a predominant representation of the younger population, as seen with the age groups. Next were the employed respondents (35.5%), followed by a smaller percentage of entrepreneurs (2.9%). Additionally, only one respondent reported being disabled, and seven were unemployed.

Table 2. Sociodemographic characteristic.

Variable	Male	Female	Prefer Not to Disclose	Total
Gender	193 (50.4%)	185 (48.3%)	5 (1.3%)	383
Age				
Younger than 18 years	5 (2.6%)	5 (2.7%)	1 (20%)	11 (2.9%)
18–24 years	67 (34.7%)	69 (37.3%)	1 (20%)	137 (35.8%)
25–34 years	73 (37.8%)	49 (26.5%)	1 (20%)	123 (32.1%)
35–44 years	24 (12.4%)	37 (20%)	1 (20%)	62 (16.2%)
45–54 years	17 (8.8%)	19 (10.3%)	1 (20%)	37 (9.7%)
55–64 years	5 (2.6%)	6 (3.2%)	0 (0%)	11 (2.9%)
Older than 65 years	2 (1%)	0 (0%)	0 (0%)	2 (0.5%)
Educational background				
Less than a high school diploma	2 (1%)	3 (1.6%)	0 (0%)	5 (1.3%)
High school diploma	44 (22.8%)	45 (34.5%)	1 (20%)	90 (23.5%)
Bachelor's degree	55 (28.5%)	55 (29.7%)	2 (40%)	112 (29.2%)
Master's degree	70 (36.3%)	68 (36.8%)	2 (40%)	140 (36.6%)
Doctorate	22 (11.4%)	14 (7.6%)	0 (0%)	36 (9.4%)
Job				
Student	122 (63.2%)	96 (51.9%)	2 (40%)	220 (57.4%)
Employed	55 (28.5%)	79 (42.7%)	2 (40%)	136 (35.5%)
Entrepreneur	8 (4.1%)	3 (1.6%)	0 (0%)	11 (2.9%)
Retired	5 (2.6%)	3 (1.6%)	0 (0%)	8 (2.1%)
Disabled	0 (0%)	0 (0%)	1 (20%)	1 (0.3%)
Unemployed	3 (1.6%)	4 (2.2%)	0 (0%)	7 (1.8%)

4.2. Cycling Characteristics

Table 3 shows the cycling characteristics of respondents. The survey found that cycling is the most popular mode of transport among males and females, with over 50% of respondents choosing it as their preferred option for traveling in the city. Bicycle experience varied, with the majority having cycled for over 10 years. Daily cycling distances ranged from less than 1 km to over 10 km, with the 2–5 km range being the most common. Weekly cycling frequency also varied, with most people cycling between 3 and 5 days a week.

Table 3. Cycling characteristics of respondents.

Variable	Male	Female	I Prefer Not to Disclose	Total (%)
Frequent mode of transport				
Car	20 (10.4%)	21 (11.4%)	0 (0.0%)	41 (10.7%)
Scooter	0 (0.0%)	1 (0.5%)	1 (20.0%)	2 (0.5%)
Public transport	18 (9.3%)	25 (13.5%)	0 (0.0%)	43 (11.2%)
Bicycle	119 (61.7%)	95 (51.4%)	3 (60.0%)	217 (56.7%)
Foot	36 (18.7%)	43 (23.2%)	1 (20.0%)	80 (20.9%)
Biking experience				
Less than one year	15 (7.8%)	20 (10.8%)	0 (0.0%)	35 (9.1%)
1–2 years	19 (9.8%)	11 (5.9%)	0 (0.0%)	30 (7.8%)
2–5 years	23 (11.9%)	12 (6.5%)	0 (0.0%)	35 (9.1%)
5–10 years	18 (9.3%)	24 (13.0%)	0 (0.0%)	42 (11.0%)
More than ten years	118 (61.1%)	118 (63.8%)	5 (100.0%)	241 (62.9%)
Daily average cycling distance (km)				
Less than 1 km	18 (9.3%)	26 (14.1%)	1 (20.0%)	45 (11.7%)
1–2 km	32 (16.6%)	35 (18.9%)	0 (0.0%)	67 (17.5%)
2–5 km	69 (35.8%)	51 (27.6%)	1 (20.0%)	121 (31.6%)
5–10 km	38 (19.7%)	52 (28.1%)	1 (20.0%)	91 (23.8%)
More than 10 km	36 (18.7%)	21 (11.4%)	2 (40.0%)	59 (15.4%)
Weekly cycling frequency (average number of days in a week)				
1-day	15 (7.8%)	20 (10.8%)	1 (20.0%)	36 (9.4%)
2-days	20 (10.4%)	20 (10.8%)	0 (0.0%)	40 (10.4%)
3-days	24 (12.4%)	25 (13.5%)	2 (40.0%)	51 (13.3%)
4-days	35 (18.1%)	25 (13.5%)	0 (0.0%)	60 (15.7%)
5-days	54 (28.0%)	63 (34.1%)	1 (20.0%)	118 (30.8%)
6-days	22 (11.4%)	19 (10.3%)	0 (0.0%)	41 (10.7%)
7-days	23 (11.9%)	13 (7.0%)	1 (20.0%)	37 (9.7%)

Figure 3 shows the results of the question about the purpose of bicycle use in urban areas. The respondent could choose multiple options for this question in the survey. The survey results revealed that commuting to and from work or school was the most prevalent bicycle use, with 77.30%, followed by shopping, with 49.60%. Bicycle use for leisure activities and visiting relatives or friends had a share of 43.30% and 43.10%, respectively. A small percentage (4.20%) of the participants mentioned other purposes, like taking their children to school.

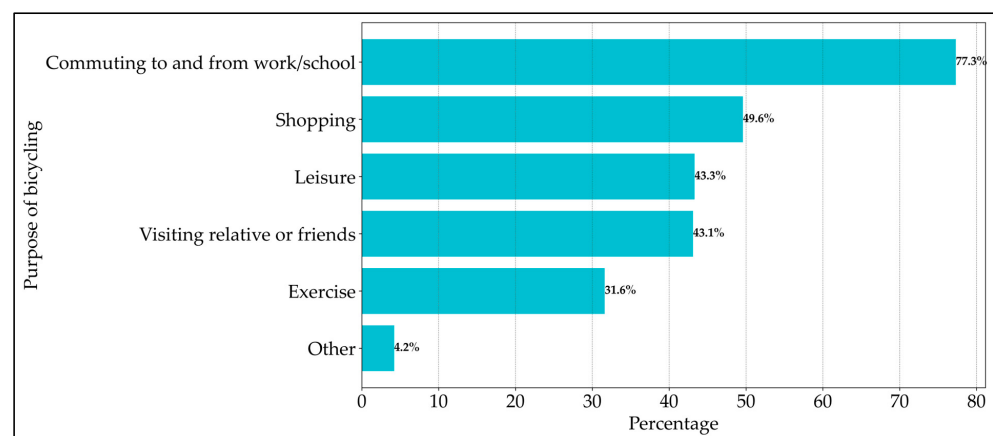


Figure 3. Purpose of bicycle use in urban areas.

4.3. Bicycle Infrastructure Indicators Importance

Figure 4 represents the respondents' rating of various bicycle infrastructure indicators on a scale of 1 to 5, with 1 being the least important and 5 being the most important. Each horizontal bar in Figure 4 corresponds to a bicycle infrastructure facility labeled on the Y-axis. The colors in each bar correspond to the ratings given, and the length of each color segment represents the percentage of respondents who gave that rating. The presence of bicycle infrastructure (PBI) received the highest 5-point rating (50.9%), followed by motorized traffic speed (TS) with 41.5%. The rating data is used in TOPSIS analysis to rank the importance of each bicycle infrastructure attribute.

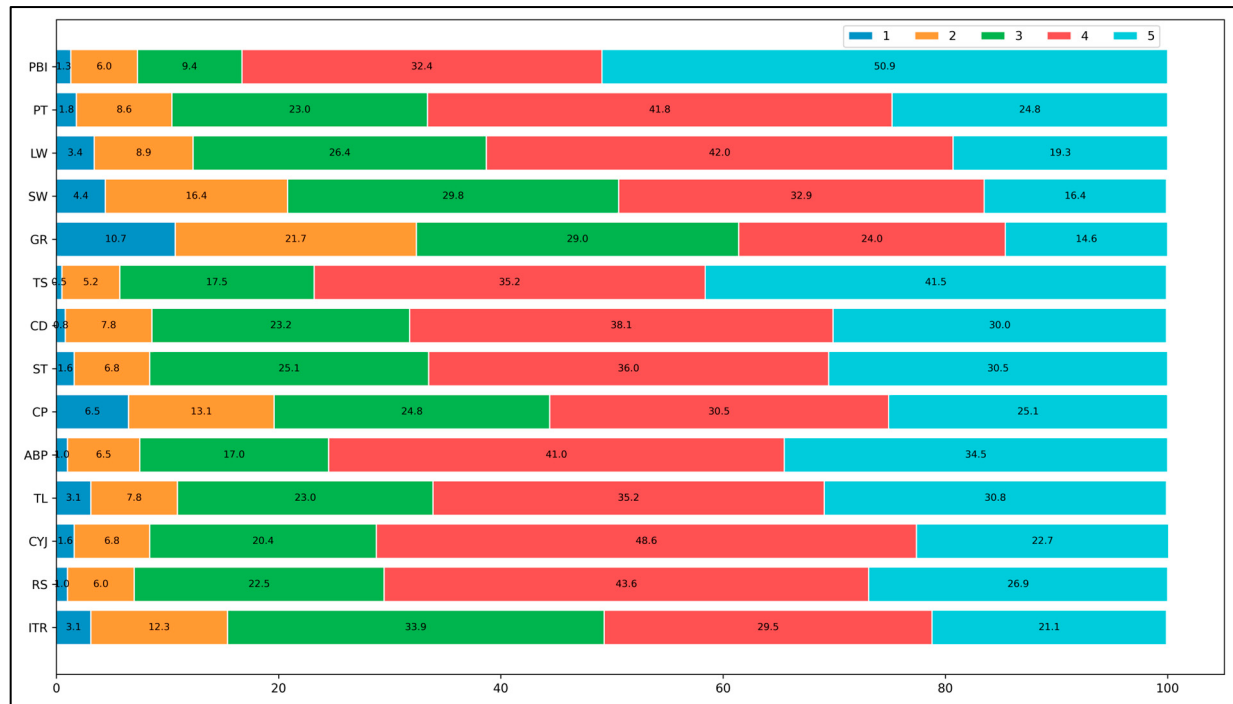


Figure 4. Bicycle infrastructure indicator importance.

4.4. TOPSIS Analysis

As reported by previous studies, the score assigned by the respondents can be used to perform TOPSIS analysis [60,62]. The scores assigned to all the bicycle infrastructure indicators were considered for the TOPSIS analysis. Fourteen bicycle infrastructure indicators were considered alternatives. The criteria for assessing the significance of bicycle infrastructure attributes in this study were represented by five Likert scale values (1, 2, 3, 4, and 5), and equal weights were used for level or criteria to determine their likelihood of selection. When employing the TOPSIS method for data analysis, the higher importance levels, such as 3, 4, and 5, were maximized, considering them positive. The lower importance levels, i.e., 1 and 2, were minimized and treated as negative to derive the ideal positive solution.

Table 4 presents the results of the TOPSIS analysis performed on the bicycle infrastructure variables. d_j^b , d_j^w and S_i values were calculated for each variable to decide on the most to least importance variable based on importance to the cyclist. The d_j^b signifies the distance from the ideal best, d_j^w is the distance from the ideal worst, and S_i is the TOPSIS score. The S_i value helps to decide the ranking of the variables, with values closer to 1 showing that the indicator is most important and values near 0 showing that the indicator is least important. Based on Table 4, the PBI, such as bicycle lanes or paths, is considered the most crucial criterion ($S_i = 0.935$).

Table 4. Bicycle infrastructure indicators importance based on TOPSIS analysis.

Variables	d_j^b	d_j^w	S_i	Ranks
PBI	0.011	0.164	0.935	1
PT	0.053	0.143	0.728	8
LW	0.072	0.127	0.638	10
SW	0.100	0.100	0.502	12
GR	0.173	0.044	0.202	14
TS	0.017	0.169	0.908	2
CD	0.040	0.158	0.796	4
ST	0.040	0.152	0.790	5
CP	0.101	0.082	0.446	13
ABP	0.031	0.158	0.834	3
TRL	0.052	0.132	0.715	9
CYJ	0.054	0.151	0.737	7
RS	0.044	0.159	0.781	6
ITR	0.074	0.126	0.631	11

The TS is considered the second important criterion ($S_i = 0.908$), followed by the availability of bicycle parking (ABP) ($S_i = 0.834$). TS is a crucial safety factor, especially when the bicycle path is next to the traffic. At the same time, the ABP is a vital attractiveness factor since bicycles need secure parking when they reach a destination. In addition, the traffic control device (CD), i.e., traffic signal ($S_i = 0.796$) and street lights (ST) ($S_i = 0.790$) along bicycle paths or lanes, are also highly important.

Grade or slop (GR) was found to have the lowest relative importance ($S_i = 0.202$, rank = 14] among fourteen variables. Car parking (CP) ($S_i = 0.446$, rank = 13], the presence of a sidewalk (SW) ($S_i = 0.502$, rank = 12), and the number of interruptions (ITR) ($S_i = 0.631$, rank = 11) also received lower importance from cyclists (see Table 4). Although the slope might decrease comfort, the results indicate that it is not an influential factor in this study. The factor contributing to this lower importance ranking might be that the study areas do not have steep slopes.

4.5. Heterogeneity in the Perceived Importance of Bicycle Infrastructure Indicators

The Mann–Whitney U test and the Kruskal–Wallis tests were employed to assess any differences in the indicators between cyclist groups, such as gender, age, daily cycling distance (km), cycling experience (years), weekly bicycle use (number of days per week), and trip nature. For interpreting the results, the hypothesis is formulated as follows:

H0 = There is no difference in the groups' perception of the importance of bicycle infrastructure element.

H1 = There is a significant difference in the groups' perception of the importance of bicycle infrastructure element.

Table 5 shows the significance values for each test variable to verify the heterogeneity. The test suggests a significant difference if the p -value is less than the significance level of 0.05. The heterogeneity in the gender was conducted only for males and females, as the sample size (5) was very small for those who did not disclose their gender. A similar issue was found for the age group older than 65, with only two respondents, which does not meet the minimum sample required for the test. Similarly, smaller sample sizes, such as those younger than 18 years (11), may affect the robustness of the statistical test, potentially leading to increased variability due to the reasons mentioned. Hence, the age categories were reorganized into four categories.

The Mann–Whitney U test results (see Table 5) reveal no statistically significant differences in bicycle infrastructure indicators, supporting the null hypothesis (H0) for gender. This indicates that perceptions of bicycle facility indicators' importance are similar across genders. In contrast, significant differences were observed based on age, cycling distance, cycling experience, weekly bicycle use, and trip nature. For example, cyclists' perceptions regarding pavement type (PT) and GR varied significantly with age and cycling

distance (km). These findings indicate that the null hypothesis (H0) is rejected for these variables based on a p -value of less than 0.05. This suggests significant differences exist in how various cyclist groups perceive the importance of different bicycle infrastructure facility attributes.

Table 5. Mann–Whitney U test and Kruskal–Wallis test significance for heterogeneity in perceived importance.

Variable	Gender	Age	Cycling Distance (km)	Cycling Experience (years)	Weekly Bicycle Use	Trip Nature
PBI	0.782	0.089	0.029	0.012	0.037	<0.001
PT	0.563	0.036	0.022	0.708	0.408	0.513
LW	0.983	0.063	0.209	0.597	0.033	0.020
SW	0.744	0.008	0.851	0.073	0.016	0.121
GR	0.87	<0.001	0.034	<0.001	0.916	0.750
TS	0.302	0.472	0.894	0.714	0.570	0.009
CD	0.708	0.070	0.446	0.123	0.544	0.021
ST	0.929	<0.001	0.533	0.211	0.757	0.443
CP	0.734	<0.001	0.623	0.463	0.008	0.917
ABP	0.751	0.588	0.047	0.878	0.173	0.039
TRL	0.847	0.389	0.116	0.526	0.138	0.012
CYJ	0.593	0.102	0.383	0.520	0.661	0.011
RS	0.901	0.447	0.581	0.203	0.768	0.137
ITR	0.139	0.032	0.120	0.061	0.101	0.186

The significance level is 0.05.

There were six bicycle facility variables: PT, SW, GR, ST, CP, and ITR, for which the perception was different based on age. Meanwhile, for other variables, no heterogeneity was found for age group. It is worth mentioning that the PBI had heterogeneity for four groups, i.e., cycling distance (km), cycling experience (years), weekly bicycle use (no. of days), and trip nature.

Similarly, GR also showed variability based on age, cycling distance (km), and cycling experience (years). At the same time, the PT had heterogeneity in age, cycling experience, cycling distance (km), and trip nature. For cycling experience, most cycling infrastructure attributes were found insignificant except for the PBI and GR. Heterogeneity was observed in four variables (PBI, PT, GR, and ABP) within the cycling distance (km) group and in four different variables (PBI, bicycle lane width (LW), SW, and CP) within the weekly bicycle use group.

The heterogeneity in perceptions of bicycle facility indicators' importance in the nature of the bicycling trip in two groups—those using bicycles for work/education (school, college, and university) and those using them for other purposes (e.g., leisure, exercise, shopping, or other) were assessed. Seven indicators were found to have significant differences in the groups' perceptions of PBI, LW, TS, CD, ABP, trees/green area and landscaping (TRL), and CYJ (bicycle facilities at traffic signals). The null hypothesis (H0) can be rejected for these infrastructure attributes, indicating differing perceptions between the two groups.

It should be noted that the Mann–Whitney U and Kruskal–Wallis tests can only analyze whether there was any difference in perceived importance across different cyclist groups. However, this approach does not yield the relative importance of the crossing facility attributes, for which significant heterogeneity in perceived importance was identified among various cyclist groups. Hence, we consider TOPSIS analysis to see the relative importance of these bicycle facility attributes for those who observed heterogeneity based on the perceptions of different bicyclist groups. This additional analysis aims to explore the variations in how bicyclist groups perceive these attributes, considering the heterogeneity in their perceived importance.

4.5.1. Effect of Age Group

The TOPSIS analysis results show distinct preferences towards bicycle infrastructure facility variables across different age groups. Considerable variation regarding the importance of indicators in all age groups can be seen in Figure 5. For the age group ≤ 24 years, the ST is most important, followed by PT. The ST was significantly important for all the age groups; however, there was variation among them. Although ST is considered important by all age groups, it is extremely important, as the TOPSIS value is near ideal ($S_i = 0.955$) by age group >45 . Other variables also see preference heterogeneity in the age groups. For example, CP along bicycle paths is the third most important factor in the age group >45 years, however it is least important ($S_i = 0.227$) among the variables to the age group 25–34 years. The GR was ranked lowest among the variables that saw heterogeneity, but the TOPSIS value is considerably high ($S_i = 0.416$) for the age group 25–34 years compared to other age groups. Similarly, ITR is the third most important indicator for all age groups except for >45 years. However, the importance level varies across age groups as the TOPSIS score ($S_i = 0.738$) value is highest for >45 years and lowest ($S_i = 0.427$) for 25–34 years.

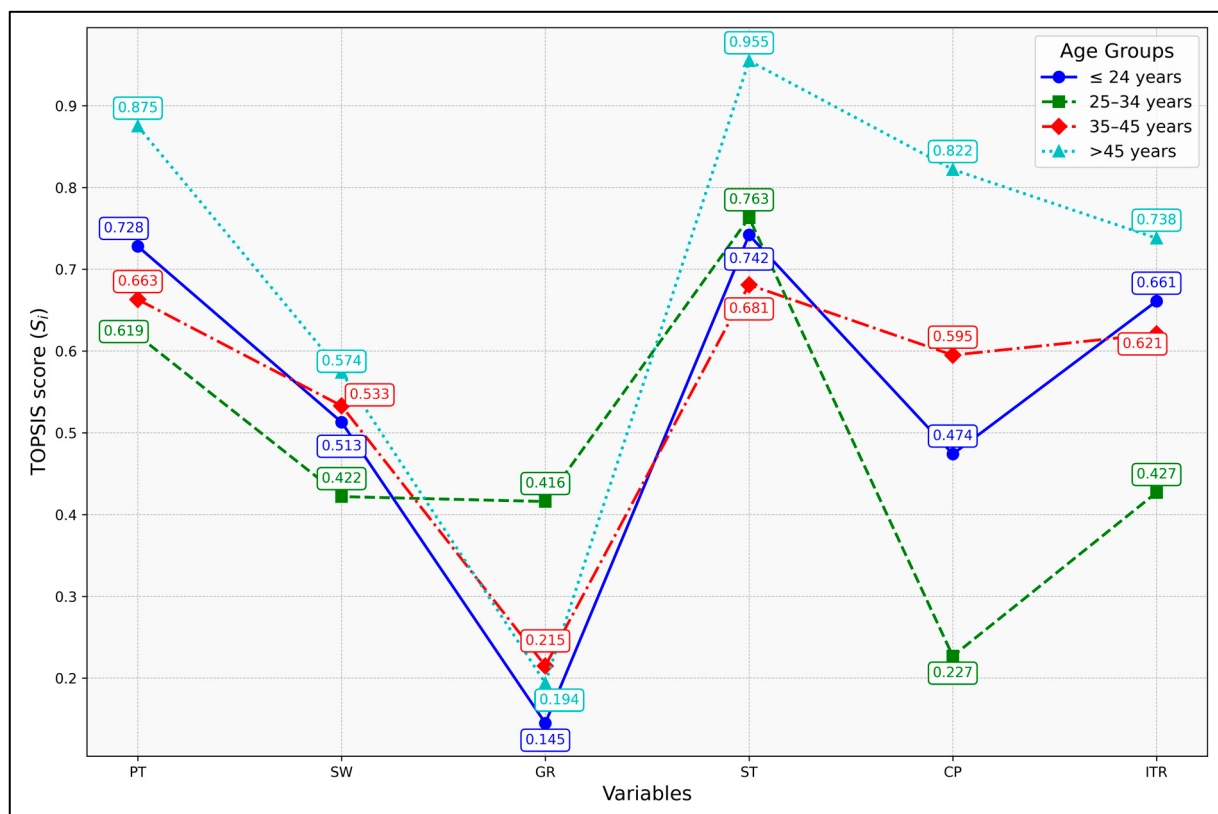


Figure 5. TOPSIS analysis for age groups.

4.5.2. Effect of Daily Bicycle Use

Figure 6 shows the results of the TOPSIS analysis performed for bicycle infrastructure indicators for cyclist groups based on daily cycling distances. For cyclists traveling more than 10 km, PBI and ABP are rated the most important, with high TOPSIS scores ($S_i = 0.993$ and $S_i = 0.845$, respectively), indicating extreme importance for longer commutes. The ABP also scores highly across all cyclist groups, particularly for cycling trips between 5 to 10 km ($S_i = 0.829$) and over 10 km ($S_i = 0.845$), suggesting that cyclists greatly value this bicycle attractiveness factor. However, the GR has consistently lower S_i values across all distances, with the highest being only 0.313 for distances less than 1 km, indicating the lowest importance. On the other hand, the PT starts with a lowest S_i value of 0.503 for

1–2 km bicycle users and shows an increase to 0.835 for distances beyond 10 km, suggesting that the pavement quality becomes more critical for cyclists on longer journeys.

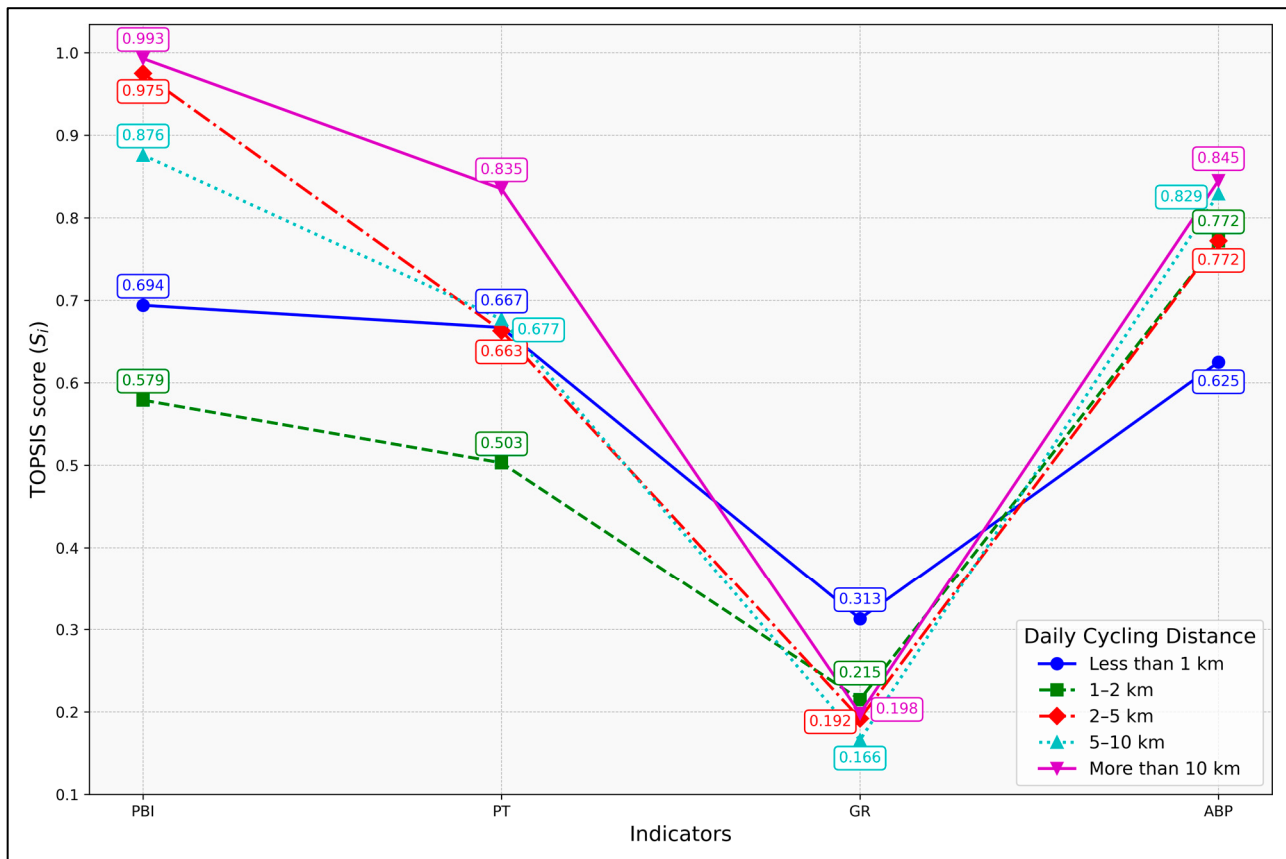


Figure 6. TOPSIS analysis for daily bicycle use.

4.5.3. Effect of Cycling Experience (Years)

The TOPSIS analysis results for cycling experience based on the number of years are shown in Figure 7. Only two factors, PBI and GR, showed heterogeneity in cycling groups based on cycling experience. For PBI, those with cycling experience of less than 1 year rate its importance $S_i = 0.634$, which significantly drops for those with 1–2 years of experience ($S_i = 0.282$), suggesting a decrease in perceived importance. The S_i for PBI is highest for cyclists with more than 10 years of experience, indicating a high perceived importance. In the case of GR, cyclists with 1–2 years of experience ($S_i = 0.723$) have the highest perceived importance, suggesting a heightened awareness or concern for path grade as cyclists gain initial experience. This perceived importance sharply decreases for those with 5–10 years of experience ($S_i = 0.117$) and more than 10 years ($S_i = 0.211$), indicating that more experienced cyclists may give less importance to the path slope.

4.5.4. Effect of Weekly Bicycle Use

The TOPSIS analysis for weekly bicycle use reveals how the perceived importance of different variables varies with the cycling frequency (Figure 8). For PBI, there is a high level of perceived importance among those who cycle just once a week ($S_i = 0.786$), and this perception increases for those who cycle 2 days a week ($S_i = 0.860$). The PBI is the least important parameter for those cycling 4 days a week ($S_i = 0.695$). In contrast, cyclists who bike 6 days a week consider this very important ($S_i = 0.990$). The variability is more noticeable for factors like SW and CP. The SW is perceived as least important by those cycling 1 and 6 days a week (S_i values of 0.395 and 0.371, respectively), but its importance increases for daily cyclists ($S_i = 0.767$). The CP has the lowest perceived importance for

5 and 6 day bicycle users ($S_i = 0.312$ and $S_i = 0.310$, respectively), while for 3-day users, it is crucial, as the TOPSIS score value increases sharply ($S_i = 0.736$). The SW becomes important for individuals who cycle 7 days a week ($S_i = 0.767$). On the other hand, for those who cycle 1 day a week ($S_i = 0.395$), the sidewalk width might not be considered crucial.

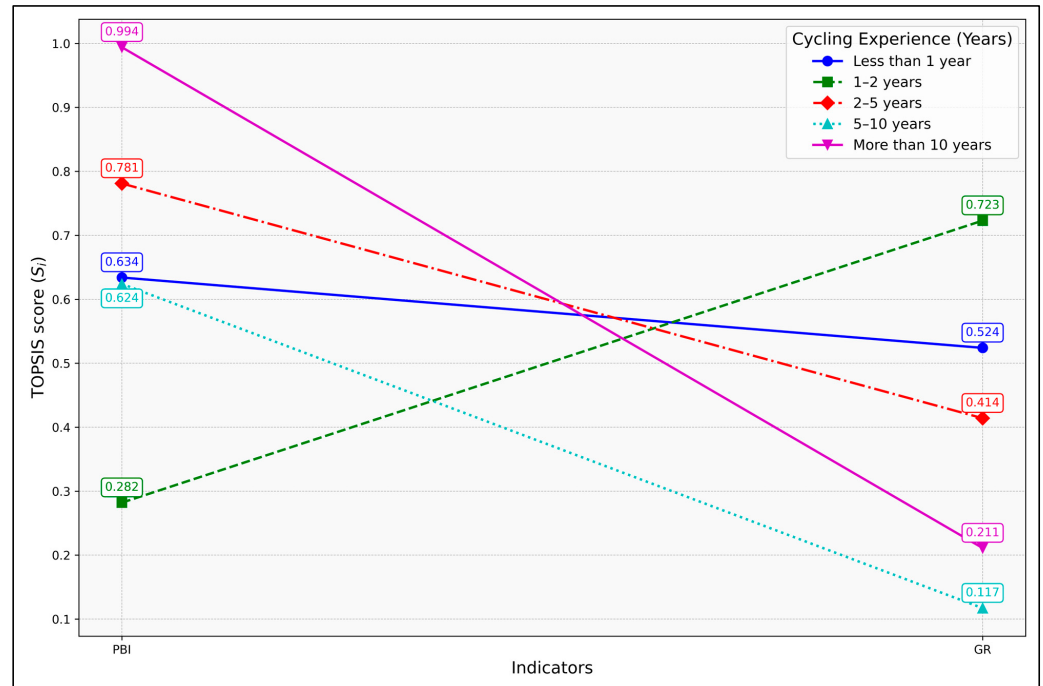


Figure 7. TOPSIS analysis for cycling experience.

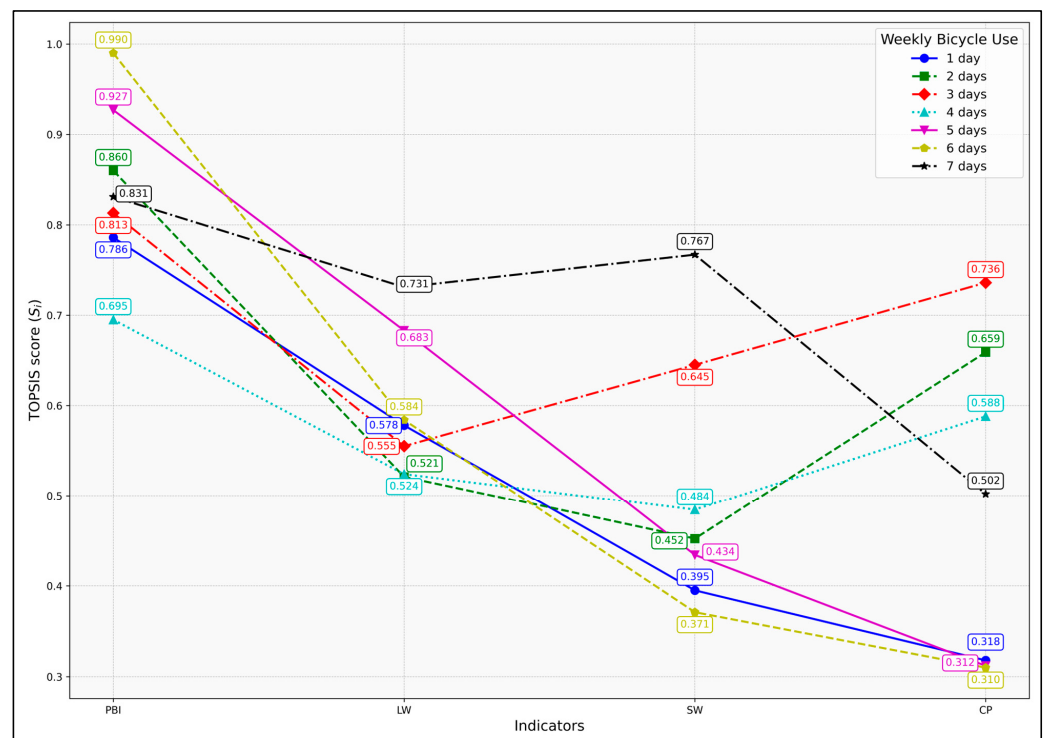


Figure 8. TOPSIS analysis for weekly bicycle use.

4.5.5. Effect of Bicycle Trip Purpose

The TOPSIS analysis results for bicycle trip purposes based on different indicators are shown in Figure 9. For education/work trips, the PBI indicator shows the highest importance ($S_i = 0.974$) but significantly drops for LW ($S_i = 0.646$), indicating lower relevance for the latter. The TOPSIS scores for TRL ($S_i = 0.812$) and TS ($S_i = 0.883$) are higher, reflecting higher importance. For other purpose trips, TS has the highest perceived importance ($S_i = 0.971$), followed by TRL ($S_i = 0.876$), while the ABP indicator shows the lowest importance ($S_i = 0.538$). The results suggest that the significance of these indicators varies depending on the purpose of the bicycle trip.

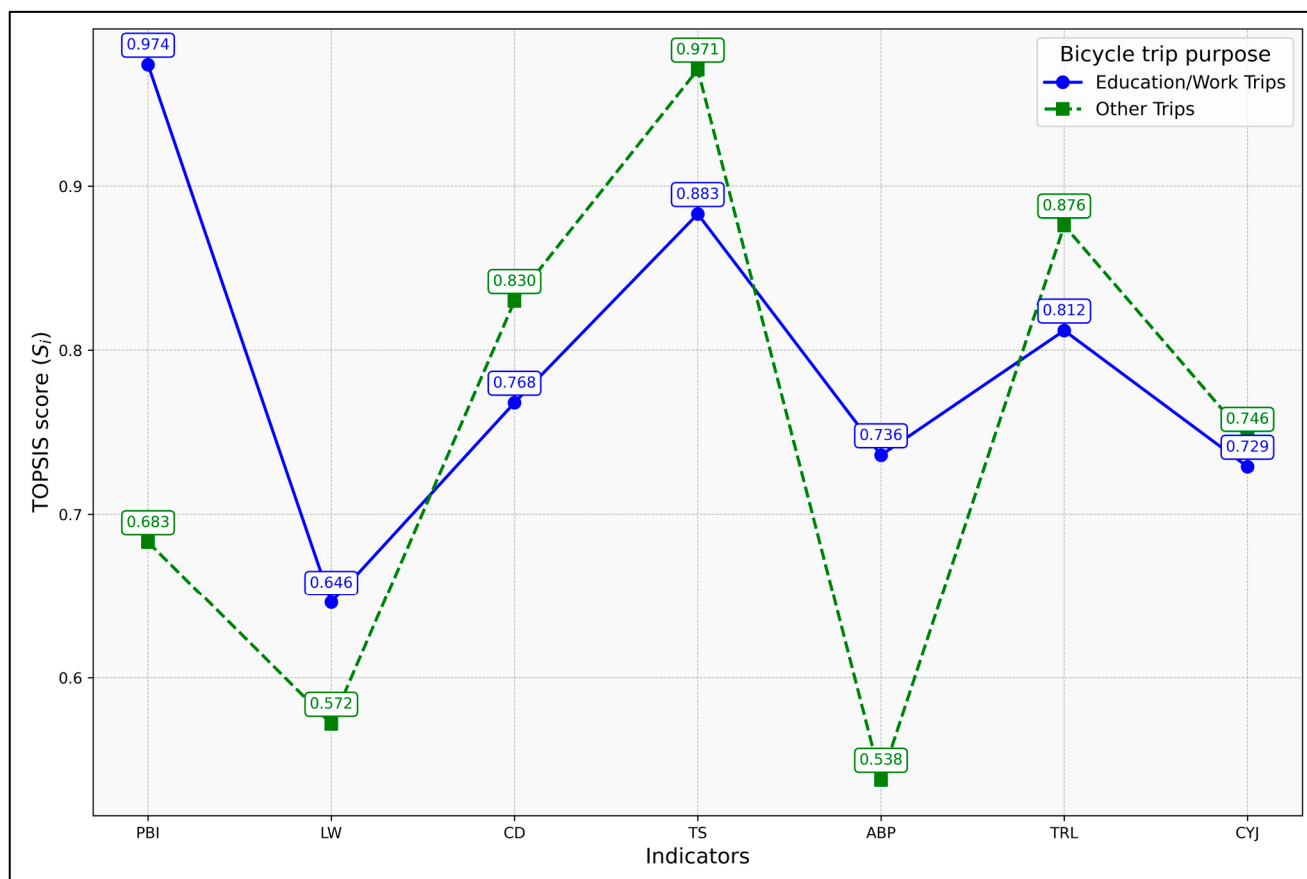


Figure 9. TOPSIS analysis for bicycle trip purpose.

5. Discussion

The study aimed to identify and rank bicycle infrastructure facility attributes based on cyclist perceptions. Cities and governments are increasingly making policies to attract more people to use bicycles [3]. For this purpose, it is crucial to know the perception of cyclists to identify the critical infrastructure variable. This identification can help the government prioritize installation and improve critical bicycle infrastructure indicators.

This study used TOPSIS to rank the attributes of bicycle infrastructure based on their importance. Consistent with previous literature, the findings emphasize that the presence of bicycle infrastructure (PBI) was ranked the most crucial facility indicated by cyclists in previous research. The PBI, i.e., bicycle lanes and paths, are essential for increasing bicyclist safety and comfort. Studies have shown that bicycle lanes, or marked bike paths, reduce crashes and injuries among cyclists [37]. The dedicated bicycle paths are critical to encouraging more people to commute by bicycle, as suggested by previous research [43]. The availability of bicycle facilities, such as bike lanes and bicycle routes and paths, is linked to increased levels of bicycle traffic [86]. This research emphasizes that traffic speed along

bicycle paths is also crucial for bicycle users. Research has found that cyclists' comfort levels are closely linked to their distance from motorized traffic [32]. Previous research also emphasizes lowering traffic speed and volume, which is expected to encourage walking and cycling [87]. Traffic speed also impacts the safety of cyclists. Higher motor vehicle speeds are reported to be associated with increased bicyclist injury severity [88].

Furthermore, the availability of bicycle parking was also found to be a critical factor, as it is ranked the third most important variable based on cyclist perception. Bicycle parking is usually considered a bicycle attractiveness feature in providing cycling infrastructure [3]. The study highlights the necessity of secure and accessible parking solutions to encourage cycling. The availability of bicycle parking has always been stressed to achieve high cycling levels. A study in the Netherlands, Denmark, and Germany emphasized the need for ample bicycle parking and other infrastructural necessities [26]. The lack of cycle parking is considered a barrier to promoting the uptake of cycling in urban areas [89].

Interestingly, the grade or slope of cycling paths has been shown to have minimal impact on cyclists' preferences in the context of this study. Cyclists usually disfavor slopes, significantly influencing cycling rates in hilly cities like San Francisco [90,91]. The area's hilliness is demonstrated as a significant deterrent for cyclists, particularly in cities with challenging topography [92]. Another study used GPS data to model cyclist route choices, revealing that even experienced cyclists avoid steep slopes when possible [93]. However, some studies have reported contrasting findings supporting our results. For example, a study conducted to see the role of the city topography and climate in cycling mode choice suggests that the slope of a cyclist's route has no significant statistical impact on their choice to cycle [94]. Similarly, a comprehensive review reported weak effects of terrain slope on cycling behaviors [95]. The low importance of the slope in our study can be explained by the respondents' extensive cycling experience and daily use patterns. Most respondents (62.9%) have been using bicycles in the city for more than ten years, suggesting they are highly accustomed to the city's terrain and have adapted to the local terrain over many years. In addition, most respondents cycle relatively short to medium distances daily, either 2–5 km (31.6%) or 5–10 km (23.8%). Moreover, the flatness of the study areas can be one of the reasons why cyclists consider it the least important. Moreover, in Belgium, the rise in e-bike popularity is evident, as 51% of new bicycles sold in 2023 were e-bikes, and a recent report indicates that over a quarter of the population actively uses them [96]. The low slope ranking in our study may be linked to the possibility of e-bike users participating in the study.

The study also investigated the perceptions of different cyclist groups towards the infrastructural indicators. No heterogeneity was found in bicycle infrastructure indicators based on gender. Previous studies have contrasting results, as women have stronger preferences for greater separation from motor traffic [97]. In addition, the literature suggests that female commuter cyclists prefer routes with maximum separation from motorized traffic, suggesting that improved cycling infrastructure is crucial for increasing bicycle use among under-represented groups like women [98]. In our study, descriptive statistics showed that male and female cyclists use bicycles for the same purpose. Also, no significant difference is found in bicycle frequency and distance, which can be associated with why no difference was found towards bicycle facilities. Other cyclist groups based on frequency and experience level significantly influence the prioritization of infrastructure attributes. Dedicated infrastructure is more important to experienced cyclists than grade while the grade becomes important for those who have started cycling recently. Older cyclists prefer high-quality pavement, reflecting a higher sensitivity to a comfortable cycling environment.

Moreover, cyclists with longer daily commute distances emphasize the presence of dedicated cycling lanes, pavement type, and bicycle parking availability, suggesting that infrastructure availability and quality become increasingly critical for longer journeys. Various studies have found that pavement quality significantly affects cyclists' comfort [70]. In longer commutes, cyclists are more exposed to vibration generated from bicycle path irregularities, affecting their health [99]. For this reason, cyclists give more importance to

the pavement type. This study highlighted that the slope of the bicycle path is significant for newer cyclists (bicycling experience up to 2 years) as they tend to be more affected by the physical demands of cycling. Lastly, the cycling frequency also appears to impact the perceived importance of bicycle infrastructure indicators. Frequent cyclists may value the presence of dedicated infrastructure more highly, possibly as a factor that influences their decision to cycle. It is also important for new riders as well. Dedicated bicycle infrastructure, such as lanes or bicycle paths, has been identified as the key to attracting new cyclists [90].

6. Conclusions

Cities worldwide are looking to bicycles as a sustainable and healthy transportation option, but attracting more people requires understanding their needs and preferences. This study aimed to investigate the critical bicycle infrastructure elements and explore heterogeneity among different cycling groups towards the infrastructure elements. We explored the relatively unexplored area of cyclist heterogeneity, analyzing how various demographic and experiential factors influence perceptions of bicycle facilities. In addition, the survey was conducted in a city with good bicycle infrastructure, and the respondents were well aware of the bicycle facilities. Moreover, by focusing on cyclists familiar with existing facilities, we gather informed opinions that can guide practical improvements and planning for new bicycle infrastructure.

The results suggested that bicycle infrastructure (e.g., lanes, bicycle paths, etc.) emerged as cyclists' top priority. It reflects that cyclists value the safety and comfort provided by separation from motor traffic, aligning with findings from previous research. Similarly, secure and accessible bicycle parking ranked high, highlighting its crucial role in preventing vandalism and theft. The results also emphasized that high-quality pavement is essential, minimizing discomfort and contributing to a smoother, more enjoyable ride.

Interestingly, the study found no significant difference in preferences based on gender, contrary to some studies suggesting a stronger female preference for segregation from traffic. Cyclists who commute longer valued dedicated lanes and pavement quality more, highlighting the importance of infrastructure for longer journeys. Infrequent cyclists emphasized dedicated infrastructure more, suggesting it could attract new riders. Although the city grade or slope is the least important indicator in the study, it is still important to new cyclists. The finding helps urban planners and policymakers consider the relevant bicycle facilities based on demographic characteristics and bicyclist users in the city. Policymakers should prioritize the development of bicycle lanes and high-quality pavement to enhance overall cyclist comfort and safety. Improving traffic speed regulations and ensuring adequate separation from motor vehicles will address critical safety concerns. Implementing secure bike parking facilities at important destinations like train stations, bus stops, government offices, and key commercial places will address concerns about theft and vandalism.

Additionally, integrating other infrastructural elements, such as bicycle traffic signals and enhancing street lighting, will improve safety and visibility, particularly at intersections and during low-light conditions. This will help create cycling environments that not only address the diverse requirements of cyclists but also foster a more inclusive and supportive cycling culture. The suggested recommendation helps attract and retain a diverse range of cyclists, fostering a supportive and sustainable cycling culture.

While providing important findings into cyclists' preferences, this study has several limitations that should be acknowledged. Going forward, research should examine the perception of bike infrastructural elements in different topographical settings and bicycle user types (e-bike and regular bike users). Such research could highlight the significance of factors like slope, surface quality, and route connectivity that vary between different environments. This study does not differentiate between regular and e-bike users, which may affect the assessment of cyclists' preferences for infrastructural indicators. Moreover, the perception survey method might be subject to biases, such as overestimating vari-

able importance, which could distort results. Future studies could incorporate objective measures alongside self-reported data to provide a more balanced analysis.

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References

1. Monga, M.; Sadhukhan, S. Quantifying Perceived Social Benefit of Bicycle-Friendly Infrastructure in Indian Cities: Patna as a Case Study. *J. Cycl. Micromobility Res.* **2023**, *1*, 100003. [\[CrossRef\]](#)
2. Woodcock, J.; Banister, D.; Edwards, P.; Prentice, A.M.; Roberts, I. Energy and Transport. *Lancet* **2007**, *370*, 1078–1088. [\[CrossRef\]](#)
3. Ahmed, T.; Pirdavani, A.; Janssens, D.; Wets, G. Utilizing Intelligent Portable Bicycle Lights to Assess Urban Bicycle Infrastructure Surfaces. *Sustainability* **2023**, *15*, 4495. [\[CrossRef\]](#)
4. Acerra, E.M.; Shoman, M.; Imine, H.; Brasile, C.; Lantieri, C.; Vignali, V. The Visual Behaviour of the Cyclist: Comparison between Simulated and Real Scenarios. *Infrastructures* **2023**, *8*, 92. [\[CrossRef\]](#)
5. Maizlish, N.; Woodcock, J.; Co, S.; Ostro, B.; Fanai, A.; Fairley, D. Health Cobenefits and Transportation-Related Reductions in Greenhouse Gas Emissions in the San Francisco Bay Area. *Am. J. Public Health* **2013**, *103*, 703–709. [\[CrossRef\]](#)
6. Ahmed, T.; Moeinaddini, M.; Almoshaogeh, M.; Jamal, A.; Nawaz, I.; Alharbi, F. A New Pedestrian Crossing Level of Service (Pclos) Method for Promoting Safe Pedestrian Crossing in Urban Areas. *Int. J. Environ. Res. Public Health* **2021**, *18*, 8813. [\[CrossRef\]](#)
7. Sobhani, A.; Aliabadi, H.A.; Farooq, B. Metropolis-Hasting Based Expanded Path Size Logit Model for Cyclists' Route Choice Using GPS Data. *Int. J. Transp. Sci. Technol.* **2019**, *8*, 161–175. [\[CrossRef\]](#)
8. Delhoum, Y.; Belaroussi, R.; Dupin, F.; Zargayouna, M. Analysis of MATSim Modeling of Road Infrastructure in Cyclists' Choices in the Case of a Hilly Relief. *Infrastructures* **2022**, *7*, 108. [\[CrossRef\]](#)
9. Karolemeas, C.; Vassi, A.; Tsigdinos, S.; Bakogiannis, D.E. Measure the Ability of Cities to Be Biked via Weighted Parameters, Using GIS Tools. the Case Study of Zografou in Greece. *Transp. Res. Procedia* **2022**, *62*, 59–66. [\[CrossRef\]](#)
10. Cantisani, G.; Durastanti, C.; Moretti, L. Cyclists at Roundabouts: Risk Analysis and Rational Criteria for Choosing Safer Layouts. *Infrastructures* **2021**, *6*, 34. [\[CrossRef\]](#)
11. Muhs, C.D.; Clifton, K.J. Do Characteristics of Walkable Environments Support Bicycling? Toward a Definition of Bicycle-Supported Development. *J. Transp. Land Use* **2016**, *9*, 147–188. [\[CrossRef\]](#)
12. Cafiso, S.; Pappalardo, G.; Stamatiadis, N. Observed Risk and User Perception of Road Infrastructure Safety Assessment for Cycling Mobility. *Infrastructures* **2021**, *6*, 154. [\[CrossRef\]](#)
13. Kellstedt, D.K.; Spengler, J.O.; Maddock, J.E. Comparing Perceived and Objective Measures of Bikeability on a University Campus: A Case Study. *SAGE Open* **2021**, *11*, 21582440211018685. [\[CrossRef\]](#)
14. Asadi-Shekari, Z.; Moeinaddini, M.; Zaly Shah, M. Non-Motorised Level of Service: Addressing Challenges in Pedestrian and Bicycle Level of Service. *Transp. Rev.* **2013**, *33*, 166–194. [\[CrossRef\]](#)
15. van Lierop, D.; Soemers, J.; Hoeke, L.; Liu, G.; Chen, Z.; Ettema, D.; Kruijff, J. Wayfinding for Cycle Highways: Assessing e-Bike Users' Experiences with Wayfinding along a Cycle Highway in the Netherlands. *J. Transp. Geogr.* **2020**, *88*, 102827. [\[CrossRef\]](#)
16. Wijaya, N.D.P.; Zubizaretta, Z.D.; Kurniasari, M.W.; Pangamiani, K. Evaluation of the Provision Of Specific Bicycle Lanes in the Malang City. *J. Innov. Civ. Eng. (JICE)* **2023**, *4*, 76–85. [\[CrossRef\]](#)
17. Parks, J.; Tanaka, A.; Ryus, P.; Monsere, C.M.; Mcneil, N.; Goodno, M. Assessment of Three Alternative Bicycle Infrastructure Quality-of-Service Metrics. *Transp. Res. Rec.* **2013**, *2387*, 56–65. [\[CrossRef\]](#)
18. McNeil, N.; Monsere, C.M.; Dill, J. Influence of Bike Lane Buffer Types on Perceived Comfort and Safety of Bicyclists and Potential Bicyclists. *Transp. Res. Rec.* **2015**, *2520*, 132–142. [\[CrossRef\]](#)
19. Nuñez, J.Y.M.; Bisconsini, D.R.; Rodrigues da Silva, A.N. Combining Environmental Quality Assessment of Bicycle Infrastructures with Vertical Acceleration Measurements. *Transp. Res. Part A Policy Pract.* **2020**, *137*, 447–458. [\[CrossRef\]](#)
20. Tainio, M.; de Nazelle, A.J.; Götschi, T.; Kahlmeier, S.; Rojas-Rueda, D.; Nieuwenhuijsen, M.J.; de Sá, T.H.; Kelly, P.; Woodcock, J. Can Air Pollution Negate the Health Benefits of Cycling and Walking? *Prev. Med.* **2016**, *87*, 233–236. [\[CrossRef\]](#)
21. Hull, A.; Holleran, C.O. Bicycle Infrastructure : Can Good Design Encourage Cycling ? *Urban Plan Transp. Res.* **2014**, *2*, 369–406. [\[CrossRef\]](#)

22. Winters, M.; Zanotto, M.; Butler, G. The Canadian Bikeway Comfort and Safety (Can-Bics) Classification System: A Common Naming Convention for Cycling Infrastructure. *Health Promot. Chronic Dis. Prev. Can.* **2020**, *40*, 288–293. [\[CrossRef\]](#) [\[PubMed\]](#)
23. Pucher, J.; Dill, J.; Handy, S. Infrastructure, Programs, and Policies to Increase Bicycling: An International Review. *Prev. Med.* **2010**, *50*, S106–S125. [\[CrossRef\]](#) [\[PubMed\]](#)
24. Kirner Providelo, J.; da Penha Sanches, S. Roadway and Traffic Characteristics for Bicycling. *Transportation* **2011**, *38*, 765–777. [\[CrossRef\]](#)
25. La Paix, L.; Cherchi, E.; Geurs, K. Role of Perception of Bicycle Infrastructure on the Choice of the Bicycle as a Train Feeder Mode. *Int. J. Sustain. Transp.* **2021**, *15*, 486–499. [\[CrossRef\]](#)
26. Pucher, J.; Buehler, R. Making Cycling Irresistible: Lessons from the Netherlands, Denmark and Germany. *Transp. Rev.* **2008**, *28*, 495–528. [\[CrossRef\]](#)
27. Fernández-Heredia, Á.; Monzón, A.; Jara-Díaz, S. Understanding Cyclists' Perceptions, Keys for a Successful Bicycle Promotion. *Transp. Res. Part A Policy Pract.* **2014**, *63*, 1–11. [\[CrossRef\]](#)
28. Akar, G.; Clifton, K.J. Influence of Individual Perceptions and Bicycle Infrastructure on Decision to Bike. *Transp. Res. Rec.* **2009**, *2140*, 165–172. [\[CrossRef\]](#)
29. Asadi-shekari, Z.; Moeinaddini, M.; Zaly, M. Pedestrian Safety Index for Evaluating Street Facilities in Urban Areas. *Saf. Sci.* **2015**, *74*, 1–14. [\[CrossRef\]](#)
30. Pucher, J. Cycling Safety on Bikeways vs. Roads. *Transp. Q.* **2001**, *55*, 9–11.
31. Adinarayana, B.; Kasinayana, B. Bicycle Safety Index for Bicycle Level of Service on Urban Streets with Extreme Mixed Weather Conditions. *Innov. Infrastruct. Solut.* **2022**, *7*, 248. [\[CrossRef\]](#)
32. Caviedes, A.; Figliozzi, M. Modeling the Impact of Traffic Conditions and Bicycle Facilities on Cyclists' on-Road Stress Levels. *Transp. Res. Part F Traffic Psychol. Behav.* **2018**, *58*, 488–499. [\[CrossRef\]](#)
33. Scarano, A.; Rella Riccardi, M.; Mauriello, F.; D'Agostino, C.; Pasquino, N.; Montella, A. Injury Severity Prediction of Cyclist Crashes Using Random Forests and Random Parameters Logit Models. *Accid. Anal. Prev.* **2023**, *192*, 107275. [\[CrossRef\]](#)
34. DiGioia, J.; Watkins, K.E.; Xu, Y.; Rodgers, M.; Guensler, R. Safety Impacts of Bicycle Infrastructure: A Critical Review. *J. Saf. Res.* **2017**, *61*, 105–119. [\[CrossRef\]](#)
35. Cobb, D.P.; Jashami, H.; Hurwitz, D.S. Bicyclists' Behavioral and Physiological Responses to Varying Roadway Conditions and Bicycle Infrastructure. *Transp. Res. Part F Traffic Psychol. Behav.* **2021**, *80*, 172–188. [\[CrossRef\]](#)
36. Lizana, M.; Tudela, A.; Tapia, A. Analysing the Influence of Attitude and Habit on Bicycle Commuting. *Transp. Res. Part F Traffic Psychol. Behav.* **2021**, *82*, 70–83. [\[CrossRef\]](#)
37. Reynolds, C.C.; Harris, M.A.; Teschke, K.; Crompton, P.A.; Winters, M. The Impact of Transportation Infrastructure on Bicycling Injuries and Crashes: A Review of the Literature. *Environ. Health* **2009**, *8*, 47. [\[CrossRef\]](#) [\[PubMed\]](#)
38. de Geus, B.; De Bourdeaudhuij, I.; Jannes, C.; Meeusen, R. Psychosocial and Environmental Factors Associated with Cycling for Transport among a Working Population. *Health Educ. Res.* **2008**, *23*, 697–708. [\[CrossRef\]](#)
39. Handy, S.L.; Xing, Y. Factors Correlated with Bicycle Commuting: A Study in Six Small US Cities. *Int. J. Sustain. Transp.* **2011**, *5*, 91–110. [\[CrossRef\]](#)
40. Milakis, D. Will Greeks Cycle? Exploring Intention and Attitudes in the Case of the New Bicycle Network of Patras. *Int. J. Sustain. Transp.* **2015**, *9*, 321–334. [\[CrossRef\]](#)
41. Dill, J.; Mohr, C.; Ma, L. How Can Psychological Theory Help Cities Increase Walking and Bicycling? *J. Am. Plan. Assoc.* **2014**, *80*, 36–51. [\[CrossRef\]](#)
42. Xing, Y.; Volker, J.; Handy, S. Why Do People like Bicycling? Modeling Affect toward Bicycling. *Transp. Res. Part F Traffic Psychol. Behav.* **2018**, *56*, 22–32. [\[CrossRef\]](#)
43. Carr, T.; Dill, J. Bicycle Commuting and Facilities in Major U.S. Cities: If You Build Them, Commuters Will Use Them. *Transp. Res. Rec.* **2003**, *1828*, 116–123.
44. Monsere, C.; Dill, J.; McNeil, N.; Clifton, K.; Foster, N.; Goddard, T.; Berkow, M.; Gilpin, J.; Voros, K.; van Hengel, D.; et al. *Lessons from the Green Lanes: Evaluating Protected Bike Lanes in the U.S. NITC-RR-583*; Transportation Research and Education Center (TREC): Portland, OR, USA, 2014. [\[CrossRef\]](#)
45. Monsere, C.M.; McNeil, N.W.; Sanders, R.L. User-Rated Comfort and Preference of Separated Bike Lane Intersection Designs. *Transp. Res. Rec.* **2020**, *2674*, 216–229. [\[CrossRef\]](#)
46. Foster, N.; Monsere, C.M.; Dill, J.; Clifton, K. Level-of-Service Model for Protected Bike Lanes. *Transp. Res. Rec.* **2015**, *2520*, 90–99. [\[CrossRef\]](#)
47. Heinen, E.; Maat, K.; Van Wee, B. The Role of Attitudes toward Characteristics of Bicycle Commuting on the Choice to Cycle to Work over Various Distances. *Transp. Res. Part D Transp. Environ.* **2011**, *16*, 102–109. [\[CrossRef\]](#)
48. Fuller, D.; Gauvin, L.; Kestens, Y.; Daniel, M.; Fournier, M.; Morency, P.; Drouin, L. Use of a New Public Bicycle Share Program in Montreal, Canada. *Am. J. Prev. Med.* **2011**, *41*, 80–83. [\[CrossRef\]](#)
49. Puello, L.L.P.; Geurs, K. Modelling Observed and Unobserved Factors in Cycling to Railway Stations: Application to Transit-Oriented-Developments in the Netherlands. *Eur. J. Transp. Infrastruct. Res.* **2015**, *15*, 27–50.
50. Reibstein, D.J.; Lovelock, C.H.; Dobson, R. de P. The Direction of Causality between Perceptions, Affect, and Behavior: An Application to Travel Behavior. *J. Consum. Res.* **1980**, *6*, 370–376. [\[CrossRef\]](#)

51. Di Salvo, R.; Galletta, A.; Belcore, O.M.; Villari, M. Modeling Users' Performance: Predictive Analytics in an IoT Cloud Monitoring System. In Proceedings of the Advances Service-Oriented and Cloud Computing: In Proceedings of the Service-Oriented and Cloud Computing: 8th IFIP WG 2.14 European Conference, ESOC 2020, Heraklion, Greece, 28–30 September 2020; pp. 149–158.
52. Comi, A.; Polimeni, A. Assessing Potential Sustainability Benefits of Micromobility: A New Data Driven Approach. *Eur. Transp. Res. Rev.* **2024**, *16*, 19. [\[CrossRef\]](#)
53. Kothari, C.R. *Research Methodology: Methods and Techniques*; New Age International: New Delhi, India, 2004; ISBN 81-224-1522-9.
54. Gibbons, J.D.; Chakraborti, S. *Nonparametric Statistical Inference: Revised and Expanded*; CRC Press: Boca Raton, FL, USA, 2014; ISBN 0-203-91156-3.
55. Sheskin, D.J. *Handbook of Parametric and Nonparametric Statistical Procedures*; Chapman and Hall/CRC: Boca Raton, FL, USA, 2003; ISBN 0-429-18616-9.
56. Kant, R.; Sadhukhan, S.; Anbanandam, R. Measuring Heterogeneity in Pedestrians' Perceived Importance towards Crossing Facilities: An Experience in Roorkee. *Transp. Res. Part F Traffic Psychol. Behav.* **2024**, *106*, 257–275. [\[CrossRef\]](#)
57. Sadhukhan, S.; Banerjee, U.K.; Maitra, B. Preference Heterogeneity towards the Importance of Transfer Facility Attributes at Metro Stations in Kolkata. *Travel Behav. Soc.* **2018**, *12*, 72–83. [\[CrossRef\]](#)
58. Rosner, B.; Glynn, R.J. Power and Sample Size Estimation for the Wilcoxon Rank Sum Test with Application to Comparisons of C Statistics from Alternative Prediction Models. *Biometrics* **2009**, *65*, 188–197. [\[CrossRef\]](#)
59. Awasthi, A.; Chauhan, S.S.; Omrani, H. Application of Fuzzy TOPSIS in Evaluating Sustainable Transportation Systems. *Expert. Syst. Appl.* **2011**, *38*, 12270–12280. [\[CrossRef\]](#)
60. Pitale, A.M.; Parida, M.; Sadhukhan, S. Location Evaluation of Existing Park-and-Ride Facilities Along a Transit Corridor: A Case of Delhi MRTS. *Transp. Dev. Econ.* **2022**, *8*, 29. [\[CrossRef\]](#)
61. Feng, C.-M.; Wang, R.-T. Performance Evaluation for Airlines Including the Consideration of Financial Ratios. *J. Air Transp. Manag.* **2000**, *6*, 133–142. [\[CrossRef\]](#)
62. Sadhukhan, S.; Banerjee, U.K.; Maitra, B. Commuters' Perception towards Transfer Facility Attributes in and around Metro Stations: Experience in Kolkata. *J. Urban Plan. Dev.* **2015**, *141*, 04014038. [\[CrossRef\]](#)
63. Codina, O.; Maciejewska, M.; Nadal, J.; Marquet, O. Built Environment Bikeability as a Predictor of Cycling Frequency: Lessons from Barcelona. *Transp. Res. Interdiscip. Perspect.* **2022**, *16*, 100725. [\[CrossRef\]](#)
64. Hardinghaus, M.; Nieland, S.; Lehne, M.; Weschke, J. More than Bike Lanes—A Multifactorial Index of Urban Bikeability. *Sustainability* **2021**, *13*, 11584. [\[CrossRef\]](#)
65. Ito, K.; Biljecki, F. Assessing Bikeability with Street View Imagery and Computer Vision. *Transp. Res. Part C Emerg. Technol.* **2021**, *132*, 103371. [\[CrossRef\]](#)
66. Schmid-Querg, J.; Keler, A.; Grigoropoulos, G. The Munich Bikeability Index: A Practical Approach for Measuring Urban Bikeability. *Sustainability* **2021**, *13*, 428. [\[CrossRef\]](#)
67. Porter, A.K.; Kohl, H.W.; Pérez, A.; Reininger, B.; Pettee Gabriel, K.; Salvo, D. Bikeability: Assessing the Objectively Measured Environment in Relation to Recreation and Transportation Bicycling. *Environ. Behav.* **2020**, *52*, 861–894. [\[CrossRef\]](#)
68. Arellana, J.; Saltarín, M.; Larrañaga, A.M.; González, V.I.; Henao, C.A. Developing an Urban Bikeability Index for Different Types of Cyclists as a Tool to Prioritise Bicycle Infrastructure Investments. *Transp. Res. Part A Policy Pract.* **2020**, *139*, 310–334. [\[CrossRef\]](#)
69. Lowry, M.; Callister, D.; Gresham, M.; Moore, B. Assessment of Communitywide Bikeability with Bicycle Level of Service. *Transp. Res. Rec.* **2012**, *2314*, 41–48. [\[CrossRef\]](#)
70. Bil, M.; Andrášik, R.; Kubeček, J. How Comfortable Are Your Cycling Tracks? A New Method for Objective Bicycle Vibration Measurement. *Transp. Res. Part C Emerg. Technol.* **2015**, *56*, 415–425. [\[CrossRef\]](#)
71. Lin, J.J.; Wei, Y.H. Assessing Area-Wide Bikeability: A Grey Analytic Network Process. *Transp. Res. Part A Policy Pract.* **2018**, *113*, 381–396. [\[CrossRef\]](#)
72. Hoedl, S.; Titze, S.; Oja, P. The Bikeability and Walkability Evaluation Table: Reliability and Application. *Am. J. Prev. Med.* **2010**, *39*, 457–459. [\[CrossRef\]](#)
73. Gu, P.; Han, Z.; Cao, Z.; Chen, Y.; Jiang, Y. Using Open Source Data to Measure Street Walkability and Bikeability in China: A Case of Four Cities. *Transp. Res. Rec.* **2018**, *2672*, 63–75. [\[CrossRef\]](#)
74. Tran, P.T.M.; Zhao, M.; Yamamoto, K.; Minet, L.; Nguyen, T.; Balasubramanian, R. Cyclists' Personal Exposure to Traffic-Related Air Pollution and Its Influence on Bikeability. *Transp. Res. Part D Transp. Environ.* **2020**, *88*, 102563. [\[CrossRef\]](#)
75. Ahmed, T.; Pirdavani, A.; Wets, G.; Janssens, D. Bicycle Infrastructure Design Principles in Urban Bikeability Indices: A Systematic Review. *Sustainability* **2024**, *16*, 2545. [\[CrossRef\]](#)
76. Beura, S.K.; Bhuyan, P.K. Development of a Bicycle Level of Service Model for Urban Street Segments in Mid-Sized Cities Carrying Heterogeneous Traffic: A Functional Networks Approach. *J. Traffic Transp. Eng.* **2017**, *4*, 503–521. [\[CrossRef\]](#)
77. Beura, S.K.; Chellapilla, H.; Bhuyan, P.K. Urban Road Segment Level of Service Based on Bicycle Users' Perception under Mixed Traffic Conditions. *J. Mod. Transp.* **2017**, *25*, 90–105. [\[CrossRef\]](#)
78. Dai, B.; Dadashova, B. Review of Contextual Elements Affecting Bicyclist Safety. *J. Transp. Health* **2021**, *20*, 101013. [\[CrossRef\]](#)
79. Arellana, J.; Saltarín, M.; Larrañaga, A.M.; Alvarez, V.; Henao, C.A. Urban Walkability Considering Pedestrians' Perceptions of the Built Environment: A 10-Year Review and a Case Study in a Medium-Sized City in Latin America. *Transp. Res.* **2020**, *40*, 183–203. [\[CrossRef\]](#)

80. Ros-McDonnell, L.; de-la-Fuente-Aragon, M.V.; Ros-McDonnell, D.; Carboneras, M.C. Development of a Biking Index for Measuring Mediterranean Cities Mobility. *Int. J. Prod. Manag. Eng.* **2020**, *8*, 21–29. [\[CrossRef\]](#)
81. Krenn, P.J.; Oja, P.; Titze, S. Development of a Bikeability Index to Assess the Bicycle-Friendliness of Urban Environments. *Open J. Civ. Eng.* **2015**, *05*, 451–459. [\[CrossRef\]](#)
82. Castañón, U.N.; Ribeiro, P.J.G. Bikeability and Emerging Phenomena in Cycling: Exploratory Analysis and Review. *Sustainability* **2021**, *13*, 2394. [\[CrossRef\]](#)
83. Likert, R. A Technique for the Measurement of Attitudes. *Arch. Psychol.* **1932**, *22*, 55.
84. Qualtrics, Provo, UT 2005. Available online: <https://www.qualtrics.com/blog/citing-qualtrics/> (accessed on 25 July 2024).
85. de Vet, H.C.W.; Mokkink, L.B.; Mosmuller, D.G.; Terwee, C.B. Spearman–Brown Prophecy Formula and Cronbach’s Alpha: Different Faces of Reliability and Opportunities for New Applications. *J. Clin. Epidemiol.* **2017**, *85*, 45–49. [\[CrossRef\]](#)
86. Le, H.T.K.; Buehler, R.; Hankey, S. Have Walking and Bicycling Increased in the US? A 13-Year Longitudinal Analysis of Traffic Counts from 13 Metropolitan Areas. *Transp. Res. Part D Transp. Environ.* **2019**, *69*, 329–345. [\[CrossRef\]](#)
87. Jacobsen, P.L.; Racioppi, F.; Rutter, H. Who Owns the Roads? How Motorised Traffic Discourages Walking and Bicycling. *Inj. Prev.* **2009**, *15*, 369–373. [\[CrossRef\]](#) [\[PubMed\]](#)
88. Liu, J.; Khattak, A.J.; Li, X.; Nie, Q.; Ling, Z. Bicyclist Injury Severity in Traffic Crashes: A Spatial Approach for Geo-Referenced Crash Data to Uncover Non-Stationary Correlates. *J. Saf. Res.* **2020**, *73*, 25–35. [\[CrossRef\]](#)
89. Ito, Y.; Morgan, M.; Lovelace, R. Where to Invest in Cycle Parking: A Portfolio Management Approach to Spatial Transport Planning. *Environ. Plan. B Urban Anal. City Sci.* **2023**, *50*, 1438–1454. [\[CrossRef\]](#)
90. Hood, J.; Sall, E.; Charlton, B. A GPS-Based Bicycle Route Choice Model for San Francisco, California. *Transp. Lett.* **2011**, *3*, 63–75. [\[CrossRef\]](#)
91. Cervero, R.; Duncan, M. Walking, Bicycling, and Urban Landscapes: Evidence From the San Francisco Bay Area. *Am. J. Public Health* **2003**, *93*, 1478–1483. [\[CrossRef\]](#) [\[PubMed\]](#)
92. Winters, M.; Davidson, G.; Kao, D.; Teschke, K. Motivators and Deterrents of Bicycling: Comparing Influences on Decisions to Ride. *Transportation* **2011**, *38*, 153–168. [\[CrossRef\]](#)
93. Broach, J.; Dill, J.; Gliebe, J. Where Do Cyclists Ride? A Route Choice Model Developed with Revealed Preference GPS Data. *Transp. Res. Part A Policy Pract.* **2012**, *46*, 1730–1740. [\[CrossRef\]](#)
94. Tyndall, J. Cycling Mode Choice amongst US Commuters: The Role of Climate and Topography. *Urban Stud.* **2020**, *59*, 97–119. [\[CrossRef\]](#)
95. Yang, Y.; Wu, X.; Zhou, P.; Gou, Z.; Lu, Y. Towards a Cycling-Friendly City: An Updated Review of the Associations between Built Environment and Cycling Behaviors (2007–2017). *J. Transp. Health* **2019**, *14*, 100613. [\[CrossRef\]](#)
96. The Brussels Times. Belgium, the Homeland of e-Bike? *Motorised Bicycle Sales Soar*. Available online: <https://www.brusselstimes.com/1001418/belgium-the-homeland-of-e-bike-motorised-bicycle-sales-soar> (accessed on 27 August 2024).
97. Aldred, R.; Elliott, B.; Woodcock, J.; Goodman, A. Cycling Provision Separated from Motor Traffic: A Systematic Review Exploring Whether Stated Preferences Vary by Gender and Age. *Transp. Rev.* **2017**, *37*, 29–55. [\[CrossRef\]](#)
98. Garrard, J.; Rose, G.; Lo, S.K. Promoting Transportation Cycling for Women: The Role of Bicycle Infrastructure. *Prev. Med.* **2008**, *46*, 55–59. [\[CrossRef\]](#) [\[PubMed\]](#)
99. Nuñez, J.Y.M.; Teixeira, I.P.; da Silva, A.N.R.; Zeile, P.; Dekoninck, L.; Botteldooren, D. The Influence of Noise, Vibration, Cycle Paths, and Period of Day on Stress Experienced by Cyclists. *Sustainability* **2018**, *10*, 2379. [\[CrossRef\]](#)

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