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Assessment methods for bicycle environment safety and comfort: A scoping review

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ABSTRACT

Bicycle use is associated with health benefits due to increased physical activity. Encouraging cycling in cities requires the establishment of supportive infrastructure. Various assessment methods have been developed to evaluate bicycle infrastructures' safety, comfort, and efficiency. This scoping review provides an overview of the methods used to assess bicycle infrastructure, as reported in relevant studies. A comprehensive literature search was conducted in three scientific databases (Web of Science, Scopus, and Google Scholar) using the PRISMA guideline extension for scoping the reviews. The retrieved articles were screened, coded, and synthesized according to the eligibility criteria. Fifty-five articles met the criteria and were included in the scoping review. The assessment methodologies primarily focused on four aspects: vibration or roughness index, Bicycle Level of Service (BLOS), Bikeability Index (BI), and Bicycle Safety Index (BSI). Questionnaires (evaluation platforms), bicycles, GIS, and video cameras were the most commonly used equipment/resources. Roughness index assessments relied on objective data, such as acceleration values, and some studies validated their findings using cyclists' subjective comfort perception. On the other hand, subjective data were predominantly used for BLOS assessment. The BIs present a more comprehensive analysis of bicycles by including more components of bicycle infrastructure design. Methodologies have been developed to evaluate various aspects of the bicycle infrastructure. However, selecting appropriate methods for specific contexts cannot be undermined. This review article provides a helpful guide on selecting an appropriate methodology for the unique characteristics of the study area that enhances the effectiveness of bicycle infrastructure evaluation.

1. Introduction

Bicycling has become vital for urban transportation worldwide. Numerous transportation agencies have encouraged the increasing trend of bicycling as they recognize the potential benefits of public health, air quality, and traffic congestion [1,2]. Bicycling helps meet the global recommended daily physical activity and has been associated with reduced risks of all-cause mortality, coronary heart disease, and diabetes [3–5]. Forecasting and modeling research has also demonstrated that bicycling offers population health benefits that outweigh adverse risks, such as air pollution [6]. Moreover, shifting from motorized transport to cycling for short, regular trips (up to 5 km oneway) has yielded significant economic benefits, including annual savings of approximately 1300 euros through improved physical health [7]. Therefore, encouraging cycling can facilitate diverse health and monetary benefits.

Providing infrastructure that supports the needs of cyclists has been considered an important strategy to encourage more cycling in cities [8, 9]. Previous studies suggest that dedicated bicycle facilities are critical to cycling, as potential cyclists strongly desire infrastructure that separates cyclists from motor vehicles [6,10]. Currently, there are many examples of how bicycle infrastructure is implemented. For instance, in addition to conventional bike lanes, cities in the United States have experimented with buffered bike lanes either as single or combined with European-style cycle tracks, a design known as “separated bicycle facilities” to distinguish motor vehicles and cyclists [11]. European countries like the Netherlands, Denmark, Sweden, and Belgium provide excellent, interconnected bicycle infrastructure to encourage bicycling. Additionally, many countries promote using bicycles as feeders for public transportation [12].

Various bicycle infrastructure conditions result in different levels of perceived comfort and safety [13,14]. Street design can significantly impact the ability to bicycle, making it crucial for urban planners to

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consider diverse user needs [15]. Creating visually appealing urban spaces with uninterrupted bicycle ways, smooth pavement, connected and well-planned bicycle facilities can further enhance the experience for those choosing to bike [16]. Various methods, such as the BLOS, BSI, and BI, have been developed to consider these factors in assessing the bicycle environment for bicyclists' safety, comfort, and overall efficiency. A few studies have also been conducted that review the developed methods. A number of review papers have been published in recent years, specifically since 2010, focusing on evaluating bicycle infrastructure assessment methods. It is crucial to note that each review article focused only on a specific type of assessment method; for example, Asadi-Shekari et al. [15] and Kazemzadeh et al. [17] considered only the bicycle LOS concept. Whereas others, for example, Castañon and Ribeiro [18] and Valenzuela et al. [19], focused on bikeability. These review articles provide a comprehensive overview of the methods developed but lack clarity on differentiating and categorizing them.

While diverse assessment methods exist for bicycle comfort and safety of the bicycle environment, a critical gap in the literature remains unaddressed: the comprehensive grouping, comparison, and selection of these methods based on specific contexts. Existing studies fail to systematically categorize methods and highlight the key differences in each category. In addition, the review articles fail to provide information on the application of these developed methods. This lack of clarity creates significant challenges for practitioners and policymakers in selecting the optimal assessment method for their specific needs. This review fills this gap by thematically grouping these methods, comparing and applicability across various scenarios.

2. Methodology

This study followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines extension and the review framework for scoping reviews [20,21].

2.1. Study design

Given the diverse study designs and methods employed in the literature, this scoping review explored the comfort and safety evaluation frameworks for various bicycle infrastructure and facility designs. The scoping reviews suit studies with broader aims and objectives [20]. The PRISMA Extension for Scoping Reviews guidelines were followed to ensure the study was systematic and transparent [21]. These guidelines assist in defining research questions, identifying exclusion and inclusion criteria, and assessing relevant and accessible scientific articles while conducting a scoping review.

2.2. Search strategy and search terms

Three search engines, Web of Science (WOS), Scopus, and Google Scholar, were employed in this study. The search was limited to studies published between 2005 and 2024. The search terms were broadly categorized as bicycling, infrastructure, and assessment methods. Alternative keywords were permitted for each component as denoted by the Boolean operator "OR." The separator "AND" combines each component with other words. These terms were searched in titles, abstracts, and keywords to minimize the risk of overlooking relevant studies. The detailed search string, developed based on the keywords below, is provided in Appendix 2.

(1) Retrieval of studies on bicycling.
   a. ("bicycle" OR "cycling" OR "bike") AND
(2) Retrieval of articles related to bicycling infrastructure.
   a. ("infrastructure" OR "facility" OR "lanes" OR "path") AND:
(3) To retrieve all relevant studies using assessment methods for bicycle infrastructure.
   a. ("assessment" OR "evaluation").

2.3. Study selection

Specific inclusion and exclusion criteria were considered in the study selection process. Irrespective of the study design, all articles written in English describing assessment methods for bicycle infrastructure were considered. Subsequently, only journal articles and research presented at conferences were considered, while review articles, reports, and book chapters were excluded. Likewise, no further evaluation was conducted for inaccessible articles. The titles and abstracts of all retrieved articles were screened for shortlisting the articles. Studies that used or computed assessment methods using a mathematical index to evaluate either comfort or safety with cycling infrastructure were considered for the final selection. The full text of the selected articles was read only after fulfilling the eligibility criteria.

Fig. 1 shows the total number of articles retrieved from the three databases. The number of papers decreased when the filtering criteria, i.e., English language, type of publication, was applied. Seven hundred eighty-two articles from the WOS, 1739 from Scopus, and the first 400 relevant articles based on titles were selected for further screening. The reason to screen the first 400 results in Google Scholar was that relevance significantly declined beyond this point. A limitation of using Google Scholar was its lack of systematic export and filtering options like WOS and Scopus, which required screening online. However, this additional step ensured that no potentially relevant studies were overlooked. The duplicates ($n = 664$) were removed, and the remaining 2257 articles were screened based on their titles and abstracts. Next, 89 articles were assessed for eligibility or full-text reading. Subsequently, 39 articles were excluded due to irrelevant study designs, unavailable documents, book chapters, and review articles. Finally, five articles were retrieved from the backward and forward reference checks. Overall, 55 articles fulfilled the inclusion criteria and were included in the present study.

2.4. Data synthesis

The extracted information included the author's information, year and country of publication, tools utilized for data collection (e.g., surveys, interviews), study sample, the scope of the study, and the assessment method used. In addition to general metadata, we extracted data directly relevant to the study objectives, such as the assessment methods' applicability, to analyze its applicability in various contexts. To categorize and synthesize the findings, we employed thematic analysis, a method used to identify, analyze, and report patterns or themes within the shortlisted articles. Themes were generated on the basis of the assessment methods used in the included studies. Thematic analyses have been used in several scoping and systematic reviews on research topics related to bicycling [22]. As this review is exploratory, an inductive approach allows themes to emerge directly from the assessment methods. The papers were examined and scrutinized for data extraction for more familiarity, followed by systematic data coding. Themes were then generated based on the assigned codes. Analyses were performed using Microsoft Excel and NVivo.

The studies were also synthesized to evaluate the time, cost, and technical skills required to execute the methods. These aspects are categorized into three levels, low, medium, and high, to facilitate method selection based on the specific context and resource availability. The time required for a method depends on several factors, including the assessment scale, the volume of data needed, and whether advanced devices like probe bikes or cameras are used for data collection. Methods with extensive data collection or complex execution phases may require significantly more time. These factors also influence the cost, particularly the resources required for devices, infrastructure, and personnel for data collection (if primary data is needed). The expertise level required varies based on the technical complexity of the method, such as setting

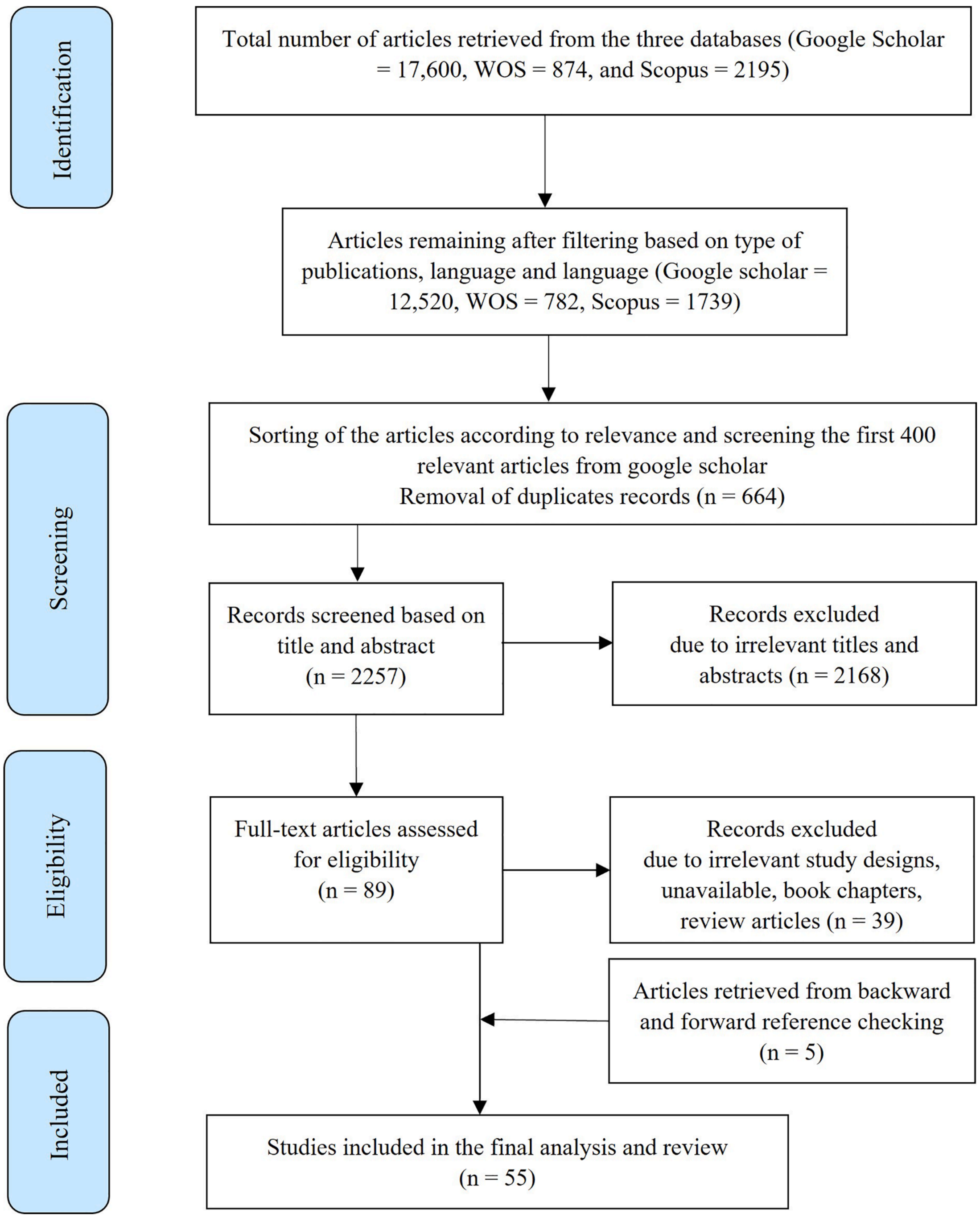

Fig. 1. Literature search and selection process using the extension of the PRISMA guidelines.

up experiments, managing data collection, and analyzing results. Low expertise' indicates that the method can be executed with basic training or general skills, such as simple data collection and processing. Medium expertise refers to methods requiring more specialized skills, such as familiarity with specific software, equipment, or basic statistical analysis. Advanced methods that involve advanced statistical models or machine learning techniques need higher technical skills.

3. Results

3.1. Geographic location of the studies

Studies developing an assessment method for bicycle infrastructure have sharply increased, with 32 of the 55 studies published published in

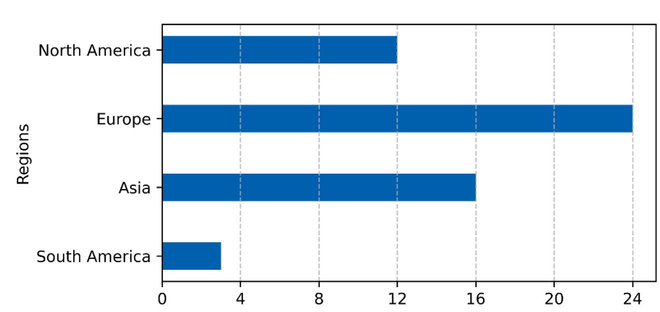

Fig. 2. Distribution of the articles based on the region.

2019 and onwards. Fig. 2 shows the region where the selected papers were conducted. Assessment methods have received a broad international presence, with many countries ($n = 23$) contributing to the research landscape. Most of the studies in this scoping review were conducted in Europe ($n = 24$), followed by Asia ($n = 16$), and North America ($n = 12$). One study has examined case studies conducted in the United States and the UK [23]. Almost half of the studies in Asia were conducted in China ($n = 7$), whereas ten of the twelve studies in North America were conducted in the USA. Fig. 3 shows the journal and conference proceedings that have published the articles reviewed. Most ($n = 8$) articles were published in Transp. Res. Part A Policy Pract. and Transportation Research Record, followed by Sustainability, which published six articles. Sensors and Case Studies on Transport Policy published two articles each. Five articles were conference proceedings, and Proceedia Engineering published two of the five in the review.

3.2. *Bicycle infrastructure assessment methods*

The themes synthesized from the review focused on the evaluated aspects of bicycle infrastructure, emphasizing the safety and comfort of the infrastructure for cyclists. The emerging themes were broadly categorized based on evaluation methods: vibration or roughness index, BLOS determination, BI, and BSI. The difference in these assessments is mainly based on the methodologies' scope. The BI assesses the overall quality of cycling conditions within a city network, reflecting on how friendly an urban area's environment is to cycling [24]. Unlike other measures focusing only on one aspect of the network, such as safety or comfort, BI considers multiple factors, including cyclists' safety, comfort levels, convenience, and attractiveness [25]. To capture this comprehensive perspective, we included studies that addressed safety, comfort, and other critical factors contributing to the overall bikeability of urban environments under this category.

Meanwhile, BLOS serves as a framework for assessing the performance of bicycle facilities [26]. The BLOS ranks various bike infrastructures, such as street segments, midblock crossings, nodes, and intersections. The assessment is based on the quality of service provided to bicyclists concerning various factors such as safety, comfort, and efficiency [15,27]. The BLOS can be measured using different indices and variables [17]. It provides an index that helps assess the quality of bicycle infrastructure in a community or city. The studies assessing the bicycle infrastructure's performance based on various metrics or indices are categorized in determining the BLOS theme.

On the other hand, the vibration or roughness index only assesses the bicycle infrastructure based on the vibration or verticle acceleration cyclists face while riding [16]. We considered studies that measure cycling comfort using the surface pavement quality of bicycle paths through vibrations experienced by cyclists as the vibration or roughness index. These measures rely on data collected via instrumented probe bicycles, smartphones, or smart bicycle lights, which capture parameters like vertical accelerations, GPS positioning, and road surface conditions. Lastly, the BSI considers only safety when evaluating the infrastructure through various variables. These studies often employ quantitative models to assess safety risks, including traffic volume, conflict risk, and road geometry. Articles in this category primarily aim to identify hazards, validate safety measures, and recommend infrastructure improvements for safer cycling environments. Table 1 summarizes the assessment methods used for bicycle infrastructure and indicators usually considered in these assessment methods.

3.2.1. *Research on vibration or roughness index*

Vibration, otherwise known as the roughness index, is a popular method for assessing the comfort quality of bicycle infrastructure. We

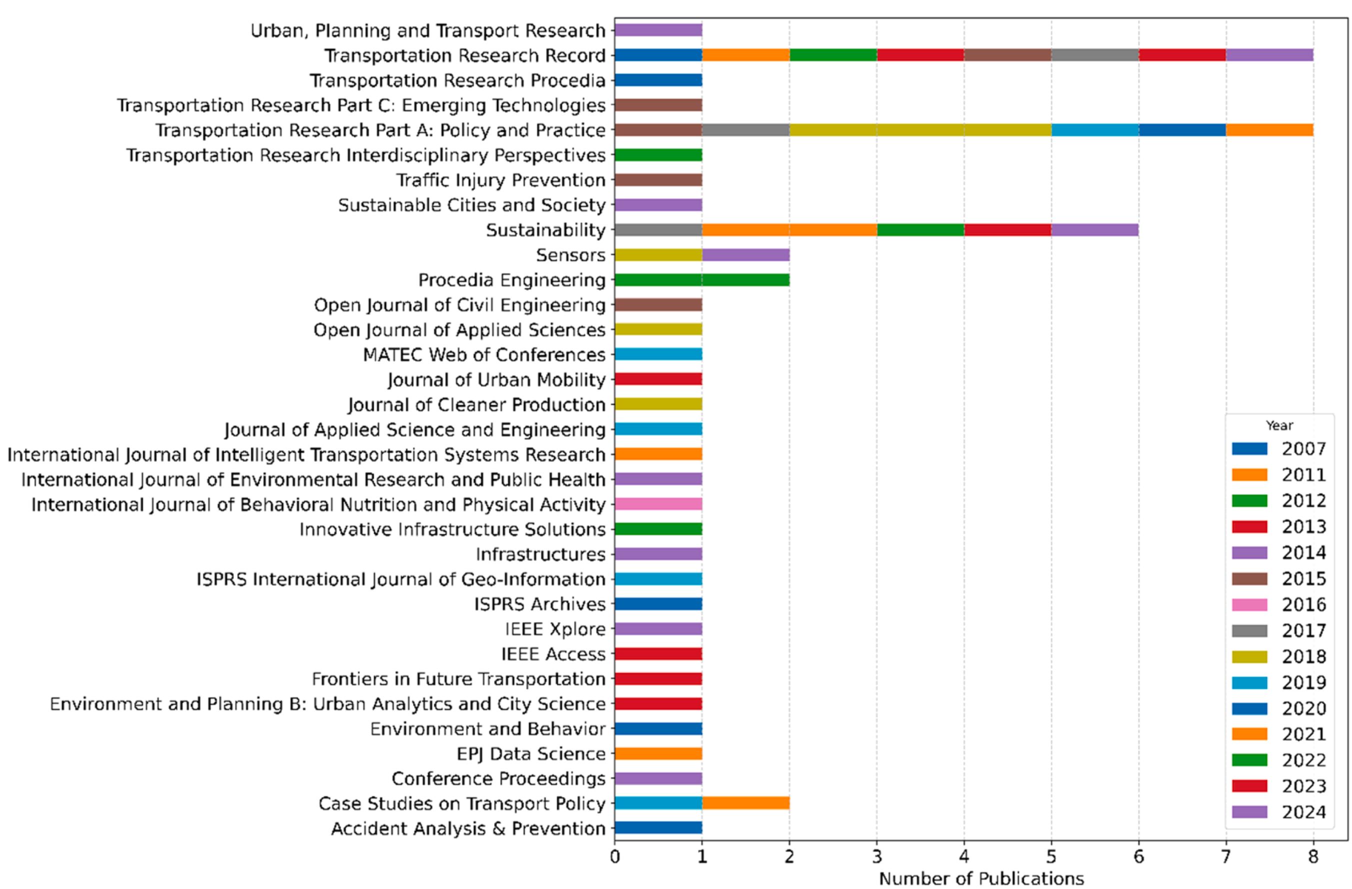

Fig. 3. Number of publications in journals.

Table 1
Key themes and evaluation methods for assessing bicycle infrastructure.

Category	Key Focus	Evaluation Method/Variables	Outcome
Vibration or roughness index	Focused on cycling comfort through pavement quality and road surface conditions.	Surface pavement quality, vertical acceleration/ vibrations.	Measures the level of comfort cyclists experience due to road conditions.
BLOS	Ranks and assesses the performance of specific bicycle facilities like streets, crossings, or intersections.	Indices and variables such as safety, comfort, efficiency, infrastructure quality, and road design.	Provides a quality index for bicycle travel and evaluates cycling infrastructure performance.
BI	A comprehensive evaluation of urban bicycle friendliness.	Multi-factor approach including cyclists' safety, comfort, convenience, coherence and attractiveness.	Assesses overall cycling conditions, reflecting how bike-friendly a city or urban area is.
BSI	Safety evaluation through models assessing risks related to infrastructure design and traffic.	Traffic volume, conflict risk, and road geometry employ crash data, traffic volume, and safety measures.	Identifies hazards, validates safety interventions, and recommends safer infrastructure.

found sixteen studies that developed the vibration or roughness index for measuring cyclists' comfort on bicycle infrastructure. Several models were used to calculate the vibration or roughness index in the relevant articles, such as the International Roughness Index (IRI), Dynamic Comfort Index (DCI), Dynamic Cycling Comfort (DCC), and Bicycle Environmental Quality Index (BEQI). Nevertheless, acceleration or vibration data is still required to support these models. Table 2 presents the summary of the research vibration or roughness index.

These studies entailed fieldwork; the most common technique applied was a bicycle mounted with GPS and accelerometer or vibration sensors [14,28–33]. Nuñez et al. [34] used the BEQI for classifying cycle paths for roughness and general conditions of the pavement surface method using a smartphone and video camera. Smartphone applications such as "RoadSR" [32] and "RideVibes" [14] have also been introduced, enabling the calculation of comfort indices like the IRI and DCI. Additionally, experiments were conducted using professional instruments to test the credibility and effectiveness of the app, such as the "RoadSR" app, which yielded positive results. Recent innovations include using low-cost devices, such as a portable bicycle light capable of measuring vibrations [16,35,36], which broadens the accessibility to vibration measurement tools. Furthermore, new approaches like the Bicycle Ride Index (BRI) were explored, combining vibration data with frequency response analysis for model calibration [37].

In addition to environmental factors, participants should have a controlled cycling manner because any abrupt changes, for example, cyclists' posture, acceleration, and speed, can influence the study results. The accidental movement of a smartphone can also affect the retrieved data. Studies have addressed challenges such as smartphone positioning and user behavior to ensure data accuracy. For instance, Zang et al. [32] and Wage et al. [14] positioned smartphones on a bicycle handlebar, which is believed to be better for minimizing the effect of accidental smartphone movement. New advancements have considered diverse instrumentation, including combining smartphones with laser profilometers to define IRI assessments [38] or incorporating advanced wearable systems like Hövding bicycle airbag helmets alongside smartphone apps [36].

Subjective and objective data have been combined in several studies to validate the results of the vibration data [16,28,29,39]. For example, Bil et al. [28] combined the DCI results from GPS data and accelerometers and surveyed cyclists' perceptions of their riding experiences. The results of the DCI and the subjectively assessed evaluations were strongly correlated. Similarly, Gao et al. [39] integrated the objective data collected using a DCC measurement system consisting of a GPS logger, acceleration logger, and smartphone mounted on a bicycle handlebar. The test vibration data (objective data) were also analyzed according to the ISO 2631 vibration standards. Another study utilized the same approach: an instrumented probe bicycle examines cycle-path conditions through user perception of satisfaction and quality [29]. Field testing was conducted using subjective user opinions and objective vibration data, which were then used to assist in the creation of dedicated user perception-based surface condition rating scales. These studies demonstrate the importance of combining these approaches for comprehensive analysis.

Table 2 shows the summary of vibration or roughness index studies. The expertise level, time, and cost of applying the methods vary for each assessment method and are influenced by collection system complexity, data collection, and analysis factors. For example, Calvey et al. [29] and Olieman et al. [31] used sophisticated systems such as the IntelliBike system, inertial acceleration sensors, and mounting brackets. However, it requires expertise to understand the experimental setup, calibration, and perception data, leading to longer timeframes and higher costs associated with conducting separate experiments and managing diverse data streams. On the other hand, studies such as Ahmed et al. [16] require medium skills because the data can easily be visualized; one only needs to understand the perception of cyclists, and the device cost is very low. Bíl et al. [28] method is intended for bicycle facility planners and road administrators. However, they must understand and combine the data collected via GPS devices and smartphone accelerometers separately, which might require high expertise.

3.2.2. Determining BLOS

The BLOS was the second evaluation method for bicycle infrastructure assessment in this review and was used in sixteen relevant studies. BLOS assesses service quality offered by road segments or bicycle facilities for cyclists. Thus, it was unsurprising as subjective evaluations were performed in twelve relevant studies relating to BLOS. Ten out of sixteen studies used video cameras on the bicycle route or segments for the users and then asked participants to rate infrastructure. This approach addresses the potential evaluation bias in different settings, e.g., traffic, roadway, and weather conditions [42]. Notably, it is argued that the method delivers results as credible as field study [43].

Some BLOS studies performed surveys by intercepting cyclists regarding their comfort perception while riding through specific study areas [13,44]. In addition, developed BLOS methods address different aspects of cycling, such as road safety, pleasant environment, and sometimes connectivity of cycling areas. A few alternative terminologies have also been used, e.g., Quality of service (QoS) [45], Level of Traffic Stress (LTS) [11], or Bicycle Compatibility Index (BCI) [46]; however, their objectives align with BLOS. In contrast, studies have evaluated the study area using video clips [11,42,43,46–48]. A video camera is frequently mounted on a bicycle to record video clips of bicycle facilities and their surroundings, and sometimes, the generated sound is recorded for a more realistic scenario.

Parks et al. [49] evaluated three alternative BLOS metrics, highlighting their strengths in assessing user comfort across various bicycle facilities, including cycle tracks and buffered lanes. Zhang et al. [50] demonstrated the utility of clustering analysis to explore cyclist behavior and lane quality under varying traffic conditions, emphasizing the adaptability of LOS measures for mixed-traffic environments. Additionally, Cabral et al. [51] highlighted the significance of connectivity and GIS-based mapping in identifying low-stress networks, demonstrating how LTS integration aligns with BLOS to enhance urban cycling infrastructure.

Innovative methods have been used in recent years, incorporating

Table 2
Summary of vibration or roughness index studies.

Authors	Assessment tool	Data Source	Scale	Study Sample and Scope	Statistical Methods and Measures	Assessment Nature	Expertise level required	Time	Cost
[37]	BRI	Experimental vibration data (accelerometer)	Low - High	4 types of bicycles tested using vibration models	Frequency response analysis, model calibration	Objective	High	Medium	Low
[35]	DCI, RMS, SEE.SENSE rating	Smartphone app, smart bicycle lights	0–1 (DCI) m/s^2 (RMS) 1–5 (SEE. SENSE)	14 streets, multiple pavement types	Wilcoxon Signed-Rank Test, Friedman Test	Objective	High	Medium	Low
[38]	IRI	Laser profilometer, accelerometer data, GPS	mm/m	660-m divided highway	Mean absolute error, mean square error, root mean square error, mean absolute percent error	Objective	High	Medium	High
[36]	DCI	Smart bicycle lights, Hövding bicycle airbag helmet, smartphone app	0–1	213,405 trips, 7236 unique users	Exponential regression model, cost-benefit analysis	Objective	High	Medium	Low
[40]	IRI, PCI, RQS	Smartphone	IRI (<2 - ≥18) PCI (0–100), RQS (<50- >150)	18.1 km test track, multiple cyclists	Pearson correlation	Objective	High	Medium	Low
[16]	Bicycle Comfort Mapping	Smart bicycle lights, smartphone app, questionnaire	5 comfort categories	20 volunteer participants (cyclists), 28 paths tested	ANOVA, Tukey HSD, Pearson correlation.	Objective and Subjective	Medium	Medium	Low
[41]	Behavioral Risk Indicator	Instrumented Bicycle, questionnaire	0–10	22 cyclists, 3.6 km route (divided into 3 zones)	Behavioral Risk Indicator calculation, normalization, descriptive statistics	Objective and Subjective	High	High	High
[14]	DCI, IRI	RideVibes smartphone app, OSM	0–1 (DCI) mm/m (IRI)	10 users, ~5000 km, 1000 trips	Comparative analysis, clustering algorithms (k-means), overlap analysis	Objective	High	Low	Low
[34]	BEQI, RMS	Video camera, Smartphone	0–100 (BEQI) m/s^2 (RMS)	5 cycle paths	Values grouping every 5 m, frequency spectrum analysis, descriptive statistics	Objective	High	Medium	Low
[33]	CCI	Instrumented Probe Bicycle	1–5	34 video clips, 100 participants, 80 road segments	Convolutional neural network, XGBoost classification algorithm, ordered probit model, variable importance analysis	Objective and Subjective	High	Low	Medium
[39]	DCC	Acceleration Data Logger, Questionnaire, smartphone app	m/s^2 (RMS) 3 comfort categories	17 volunteers, 24 urban roads (46 sections)	Reliability assessment, logistic regression, correlation analysis	Objective and Subjective	High	Medium	Medium
[32]	IRI	Smartphone accelerometer Sensor data	m/km	10 road sections	Pearson correlation, algorithm sensitivity	Objective	High	Low	Low
[28]	DCI	GPS device, Smartphone accelerometer, Questionnaire	0–1	43 cyclists, 11 street sections	Kolmogorov–Smirnov test, linear regression	Objective and Subjective	High	Medium	Medium
[29]	Surface condition rating-scale	IntelliBike, Questionnaire	1–5	75 participants for surveys, 20 for field tests, 3 routes	Exploratory Factor Analysis, Pearson correlation	Objective and Subjective	High	High	High
[30]	Rolling resistance	Pendulum	<0.35 - <0.01	1 rider, 15 m track	Linear regression, descriptive statistics	Objective	High	Low	Low
[31]	RMS	Inertial acceleration sensors, Mounting brackets, GPS	m/s^2	1 rider	root mean quad, cross-correlation	Objective	High	Low	High

virtual reality (VR) and artificial intelligence [26,52]. Some studies have integrated GIS-based analyses to digitize cyclist routes, providing a visual and statistical understanding of infrastructure performance [53]. The visual representation and analysis suggested essential improvements to bicycle infrastructure. Similarly, an innovative method for data collection, such as a web-based mapping survey, has also been utilized to improve the data collection [54]. One study used radar and video measurements for cyclists' speed and lateral distance behavior, and PTV Vissim was used for bicycle facilities and calibrated with empirical data [45].

BLOS studies highlight that variations in cyclists' acceptance of bicycle facilities are often linked to riding frequency, gender, and age [42, 48]. For example, those who ride their bicycles less often tend to be more hesitant about accepting unfavorable bicycle infrastructure. Hence, the BLOS score shows how attractive the bicycle infrastructure is to less frequent cyclists. Additionally, one study surveyed cyclists' comfort perceptions and found a positive relationship between comfort perception and cycling groups, gender, age, and environmental conditions [44]. The BLOS is also used for route choice and can assist in generating bicycle route choices [54]. The BLOS studies usually come up with a score and categorize bicycle infrastructure facilities from "A" to "F" [26,52,54]. Some studies have used other categories, such as "A" to "Eä or 1–4 [50,51]. These numbers or categories suggest critical infrastructure improvements for decision-makers [55].

Table 3 summarizes the assessment tool developed, the data source utilized, the BLOS scale used, the study sample and scope, statistical

Table 3
Summary of BLOS studies.

Authors	Assessment tool	Data Source	BLOS Scale	Study Sample and Scope	Statistical Measures	Assessment Nature	Expertise level required	Time	Cost
[45]	QoS	Radar, video recording	–	12 bicycle facilities	Goodness-of-fit test; PTV Vissim microscopic traffic flow simulations	Objective	High	High	High
[55]	BLOS	Secondary source	A-F	Cycling infrastructure across various urban roads	Regression-based modeling	Objective	Low	High	High
[52]	BLOS	Questionnaire, video recording, secondary source, survey tools, i. e., tripod stand, measuring tapes	A-F	150 cyclists (each site), 84 road segments (4 cities)	Multivariate adaptive regression splines, Genetic programming; Bayesian regularization neural network; Spearman's correlation	Objective and subjective	High	High	High
[26]	SRS	VR technologies, video recording, bicycle experimental system, rating scores	A-F	100 participants; 120 immersive, scenarios, 95 road segments	Symbolic regression; goodness of fit; percentile distribution	Objective and subjective	High	Medium	Medium
[54]	BLOS, BCI, LTS, BSL	Web-based mapping survey, secondary source	A-F (BSL, BLOS), 1–4 (LTS) 1–5 (BSL)	467 university students; 5 origin-destination pairs	GIS-based modeling; regression, detour rate optimization	Objective and subjective	Medium	Medium	Medium
[46]	BLOS, BCI	Video recording, field survey, secondary source questionnaire	A-F	200 participants (BCI), 150 participants (BLOS), main roads in city	regression analysis, correlation analysis, sensitivity analysis	Objective and subjective	Low	High	Medium
[51]	LTS	GIS, shapefiles Secondary data	1–4	20 km	Paired *t*-tests, 4.2. Network analyses, Bikeshed analysis	Objective	High	Medium	Low
[50]	LOS	Field observation, simulation data	A-E	2.25-m wide bicycle lane	Clustering analysis	Objective	Low	Medium	Medium
[11]	BLOS, LTS	Video recording, questionnaire, Google Earth, Google Maps	Poor < 0.5 $0.5 \leq$ Good $<$ 0.8 Excellent$\geq$0.8	235 participants (221 online, 14 in-person), 38 road segments	Latent Class Choice Model, Pearson correlation	Objective and subjective	High	High	High
[48]	BLOS	Video recording, questionnaire, field form	One - Five	50 participants, 42 bicycle lanes, 232 videos (63 bicycle videos chosen for rating)	Transtheoretical model, regression analysis	Objective and subjective	Low	High	Medium
[44]	BLOS	Video recording, questionnaire, field observation	A-E	1578 participants (518 e-bike, 589 e-scooter, 471 bicycle), 30 streets	Ordered probit model, Pearson's Chi-square	Objective and subjective	High	High	High
[53]	LTS	Questionnaire, hand-drawn data on a printed map	1–3	89 participants, central, 89 rasterized routes, 18,760 cells	Kruskal-Wallis H tests, Dunn's post hoc analysis, raster and vector GIS analysis	Objective and subjective	Medium	High	Medium
[42]	BLOS	Video recording, participant rating of video clips	Very poor ($\leq$2.5) - Good and fairly good ($\geq$3.5)	261 participants, 59 videos (40 road sections)	Stepwise regression analysis	Objective and subjective	Medium	High	High
[43]	BLOS	Video recording, participant rating of video clips, secondary data	A-F	221 video participants, 3230 intercept survey participants	Cumulative logistic regression, Pearson correlation, intercept survey model validation. ANOVA	Objective and subjective	Medium	High	High
[47]	CCIS	Score sheets	1–5	6 cities, case-specific infrastructure audits, 2 cyclist	Comparative score analysis	Subjective	Low	High	High
[49]	BLOS, BEQI	Video, intercept surveys	A-F (BLOS) 0–100 (BEQI)	351 cyclist, 2 bicycle facilities (center median bike lane, two-way cycle track)	Correlation analysis	Objective and subjective	Low	Medium	Medium

measures, and the expertise time and cost needed to apply the developed methods. Pritchard et al. [54] method based on BLOS and LTS is not a complicated method; however, it requires medium expertise because the data has to be collected via a web-based mapping survey and Hypertext Transfer Protocol while Network Information needs to be matched through map matching technique. Liu et al. [46] method primarily depends on data availability. If the data is available, the time can be reduced; otherwise, field surveys are necessary, which increases the time and cost of implementing the methodology. The Griswold et al. [11] method is based on a behavioral modeling approach, with data needs both quantitative and qualitative exploration. The data includes cyclists' attributes, user experience, videos, qualitative questionnaires, BLOS and LTS variables, and modeling variables, which leads to high expertise, cost, and time to implement the methodology. For the BLOS methods developed, like Shu et al. [48] and Bai et al. [44], the time depends on the sample size for the questionnaire survey. Bai et al. [44] considered 578 respondents needing more time and increased cost. Hull and O'Holleran [47] methodology of the City Cycle Infrastructure Score (CCIS) is simple and based on the cycle infrastructure score system but dependent on extensive data collection.

3.2.3. Bikeability index for measuring bicycle friendliness

The third theme in scoping review studies was BI, which assesses the bicycle infrastructure for its friendliness. Utilizing bicycle infrastructural variables is common among BI studies. The use of scoring, geographically weighted regression analysis, and the Analytic Network Process (ANP) framework in different studies highlights the adaptability of methodologies to various urban contexts [25,56]. Incorporating users' perceptions through questionnaires adds a subjective dimension to the assessment, emphasizing the importance of considering the human experience in evaluating cycling infrastructure [57,58]. However, as few studies have adopted an objective approach to BI, relying mainly on open-source data [18,59,60].

This review found fourteen articles that computed BI using bicycle infrastructural variables. Bikeability is often defined in several ways. However, it is used as a systematic tool to assess bicycle facility or area friendliness (for bicycles) and identify areas of improvement [61,62]. Spatial data and geographical information systems are mostly used to formulate the index and visualize the results. BI studies often develop analytical tools that can be used to classify areas into different groups [63]. For example, Arellana et al. [25] developed a BI incorporating directness and coherence, comfort and attractiveness, traffic safety, security, climate, bicycle infrastructure, and trip cost.

Similarly, Lin and Wei [56] computed an Area-wide bikeability assessment model (ABAM) method to evaluate zone-based friendliness to biking within an area. The key takeaway from the method was that the proposed ANP framework could be used and adjusted to incorporate the local context of a city instead of being immediately applied. The studies by McNeil [63] and Lowry et al. [62] also emphasized making destinations accessible to cyclists. Another study established a planning support system to boost bikeability in Seoul through geographically weighted regression analysis, aiming to improve equity and accessibility in transportation [64].

Tools like Bike Score® and BikeDNA have also gained prominence recently [59,65]. Bike Score® models relationships between bikeability and cycling mode share. Meanwhile, BikeDNA is an open-source tool that uses reproducible quality assessments of bicycle infrastructure data. OSM is becoming popular in BI studies for providing cycling infrastructure data [66,67]. BikeDNA proposes improvements in OSM for network research for sustainable mobility. Both tools rely on OSM data, which is increasingly popular for providing detailed cycling infrastructure information. The increasing use of open data such as OSM, Street View imagery, or OpenRouteSerive is evident in recent studies [18,60].

It is important to note that bikeability studies have included users' perceptions in the BI assessment. It is argued that the indicators used to assess bicycle infrastructure and give it a BI score have different effects on the calculation [25,58]. The perception of the cyclists or users was mainly collected through the questionnaire. However, one study used equal weight for the selected indicators [57]. One study involved experts on the importance and categorization of bikeability indicators [66]. Wahlgren and Schantz [68] included self-reported data in their Active Commuter Route Environment (ACRE) framework, demonstrating the importance of subjective factors in commuting route evaluations. Porter et al. [69] also relied on participant self-reports, GIS, and secondary data to emphasize user perception's role in determining BI scores.

Table 4 shows the summary of the developed tools. The BikeDNA is a handy tool for city managers that provides insights into bicycle infrastructure data quality by enabling straightforward exploration [59]. However, high expertise is needed to extract data from OSM sources and run the analysis to identify potential issues. Like BikeDNA, the BI developed by Wysling and Purve [67] also uses the same methodology. These methods are low-cost since they primarily depend on OSM data and secondary sources, usually government data. However, they might need time to preprocess and extract to integrate multiple data sources. Hardinghaus et al. [66] and Schmid-Querg et al. [58] provided straightforward methodologies for applicability.

3.2.4. Bicycle safety index

The fourth theme for infrastructure assessment is BSI, which emphasizes both bicycle infrastructure and the presence and volume of vehicles. Motorized traffic volume and traffic speed are consistent indicators in BSI studies. Nine articles evaluate bicycle facilities on urban streets using a BSI. Table 5 shows the summary of the BSI studies, including key aspects such as data sources, study sample, statistical measures, and other relevant details [70–72]. Most BSI studies used mixed techniques; some combined objective data with respondents' perceptions, where the respondents had to rate the selected variables for their safety. In these studies, questionnaire data were collected on the field at the selected locations to collect data from the respondents [72–75]. One study compared the proposed safety scoring methods with observed safety ratings gathered through an online questionnaire to validate the results [75]. Three studies have also utilized field observations to collect the data for the indicators [72–74]. Two studies utilized videos for data collection and later used them for ratings [76,77].

Asadi-Shekari et al. [70] adopted a point system and devised a mathematical model combining bicycle facilities and their importance. As the authors had a unique way of deciding on an indicator's importance, an indicator was considered and given more weightage in the formula if it was considered and discussed by more bicycle safety guidelines. Another multi-criteria inspection tool was developed for bicycle lane safety with the same idea; however, the weights were assigned based on the Analytic Hierarchy Process (AHP) [72]. The data for assigning the weights was collected through a questionnaire from an expert panel, including 11 technicians, nine researchers, and eight cyclists.

Adinarayana and Mir [74] developed a BSI model specifically for unsignalised three-legged junctions in urban areas, demonstrating the utility of BSI methods in high-conflict areas under mixed traffic conditions. Kamel et al. [71] introduced a composite zonal index that integrated biking attractiveness with safety, using data on cyclist-vehicle crashes and network characteristics to assess urban zones comprehensively. The scope of BSI models has been enhanced by incorporating extreme weather conditions into their analysis [73,76]. The Risk Index (RI) method [76] used an innovative approach by combining participant surveys, accelerometer data, and eye-tracking metrics for nuanced safety assessments of urban segments. Fuest et al. [75] and Daraei et al. [23] utilized open data sources such as OSM and CycleStreet, emphasizing the potential of accessible datasets for evaluating urban cycling infrastructure.

It is important to note that in BSI studies, along with bicycle infrastructure, vehicles' presence and volume are also vital for devising an index. The volume of motorized traffic is an indicator in almost all the

Table 4
Summary of BI studies.

Authors	Assessment tool	Data Source	BI Scale	Study Sample and Scope	Statistical Measures	Assessment Nature	Expertise level required	Time	Cost
[18]	Quality assessment methodology	OSM, Street View Imagery	Very low-Very High	120.2 km network, 7 Zones,	GIS-based clustering and mapping, normalization, fuzzification	Objective	High	High	Low
[59]	BikeDNA	OSM, GeoDanmark	–	Bicycle infrastructure data	Metrics based on topology, density, errors	Objective	High	Medium	Low
[60]	BI	OSM, OpenRouteService, GPS, measurement vehicles, Secondary data	0–1	City cycling network	Weighted aggregation, geospatial analysis	Objective	High	High	Medium
[67]	BI	OSM, secondary source	A-E	City-wide street segments (25,197 edges, 17,073 nodes)	Gravity-based accessibility model; suitability and accessibility model	Objective	High	Medium	Low
[66]	Multifactorial Index	OSM, expert survey	-	141 experts participants, 48,825 trips	Multinomial logit model: rho square	Objective and subjective	Low	High	Low
[58]	BI	OSM, field observations, questionnaires	1–10	10 students, cycling facilities in 100 m x 100 m spatial cell.	Weighted overlay analysis	Objective and subjective	Low	Medium	Low
[25]	BI	Google Street View, questionnaire, secondary source	0–1	336 cyclists; 585 OD survey responses, city-wide	Multinomial logit model, flow and demand modelling	Objective and subjective	Low	High	High
[69]	Transportation BI	Online self-reports (REDCap), GIS data, secondary data	1–5	998 participants	Spearman correlation, Exploratory factor analysis	Objective and subjective			
[56]	ABAM	Stakeholder interviews, questionnaire, secondary source	Worse- Best	10 cyclists (per zone), 53 administrative zones	Grey ANP, pairwise comparison, normalization	Objective and subjective	High	High	High
[65]	Bike Score®	OSM, secondary source	0–100	5664 census tracts in 24 cities	Linear regression models, multilevel modeling	Objective	Low	Medium	Low
[57]	BI	Questionnaire, secondary source	1–10	113 participants provided GPS data, 278 bicycle trips, 100 m × 100 m spatial cells	Logistic regression, Mann-Whitney U tests to assess differences	Objective and subjective	Low	Low	Low
[68]	ACRE	Self-reported questionnaire	15-point (Hindering – Stimulating)	1107 participants, suburban commuting routes	Multiple regression analysis, correlation, Sensitivity analyses	Objective and subjective	Low	High	Medium
[62]	BLOS and BI	Secondary data	A-F (BLOS) 0–1 (Bikeability)	All major bikeways in the city	Sensitivity analysis, accessibility modeling, Comparison	Objective	Medium	Medium	Low
[63]	Bikeability score	Scoring sheet, household transportation survey, secondary data	0–100	Neighborhoods, comparing 26 origin locations	Correlation analysis	Objective	Low	Medium	Low

BSI studies [70,72–74]. Additionally, several studies have considered vehicle speed to assess safety impacts [70,72].

3.3. *Equipment and resources used in the bicycle infrastructure assessment methods*

Fig. 4 shows that various equipment and tools were employed to assess various aspects of bicycle infrastructure in the selected studies. The most commonly used include questionnaires or surveys employed in 31 studies. Bicycles, the second most common tool ($n = 18$), have been predominantly employed in roughness index research. Other equipment, such as cameras and accelerometers, are often attached to bicycles for data collection purposes. GIS and cameras were vital equipment and resources, with 17 and 15 occurrences, respectively. Some studies have used technological instruments like instrumented bicycles, accelerometers, gyro sensors, and GPS devices. Studies have also employed emerging technologies, such as virtual or immersive technology. Open source data is increasingly utilized, as is evident from OSM ($n = 8$), Google Maps, open cycle map, and CycleStreet. The use of smartphone applications ($n = 8$), GPS ($n = 8$), and accelerometer ($n = 6$) are prominent technological approaches identified in the studies.

4. Discussion

The present scoping review summarizes the bicycle infrastructure assessment methods reported in the literature. This scoping review indicated a broad international interest in assessing bicycle infrastructure methods, with 55 studies conducted across 23 countries. The widespread geographic distribution of the studies suggests that different countries are actively researching and developing various approaches to

Table 5
Summary of BSI studies.

Authors	Assessment tool	Data Source	Scale	Study Sample and Scope	Statistical Measures	Assessment Nature	Expertise level required	Time	Cost
[76]	RI	Participant survey, GPS, Accelerometer, Inertial Measurement Unit, Eye Tracker, videos	0–1	Nine segments	Chi-square Test, Cramer's V, AHP	Objective and Subjective	High	High	High
[75]	Repertory Grid Score (RG), FixMyBerlin Score (FMB)	Questionnaire, secondary data, OSM, Google Maps, Open Cycle Map	1–5 (RG), 0–3 (FMB)	318 participants, 20 locations	Reliability assessment, poisson regressions	Objective and Subjective	High	Medium	Low
[73]	BSI	Field observation, questionnaire	1–6	3 road segments	Multiple linear regression	Objective and Subjective	High	High	High
[72]	Multi-criteria inspection tool	Field observation, Official records, questionnaire	0–100	3 cycle lanes, 201 cyclists, 28 experts	AHP, consistency ratios, normalization and aggregation	Objective and Subjective	High	High	Medium
[23]	Bike safety model	OSM, CycleStreet, Open Data portal	0–1	accident records (2004–2017), 3 cities	Logistic regression, Brier Skill Score, cross-city model evaluations	Objective	High	High	Medium
[71]	Bike Composite Index	Secondary sources	0–100	134 Traffic Analysis Zones	Generalized linear model, Principal components, Pearson correlation	Objective	High	Medium	Low
[74]	BSI	Field observation, questionnaire	1–5	3 un-signalized 3-legged junctions	Stepwise regression analysis, sensitivity analysis	Objective and Subjective	Low	Medium	Medium
[70]	BSI	Street guidelines	A-F	1 street and 1 road (Two countries)	Point system model, coefficients derived from guidelines	Objective	Low	Medium	Low
[77]	Bike ISI	Videos, expert survey	1–6	67 intersection approaches, 3831 cyclists observed, 129 h videos, experts	Generalized Linear Models, Poisson regression, multiple regression	Objective and Subjective	High	High	High

assess bicycle infrastructure. The scoping review mainly contributes by theming assessment methods, synthesizing the methods, and highlighting the critical gaps in the methods adopted globally. Applying thematic analysis, we categorized the methods into four main themes: vibration or roughness index, BLOS, BI, and BSI.

The assessment of bicycle infrastructure not only provides an evaluation of the already existing infrastructure but also serves as a pivotal relationship between transport planning, cyclist safety, comfort, and health, which ultimately helps promote bicycle use [5]. Active transport modes play a vital role in achieving physical activity goals, well reported in the literature [4,7]. Various assessment methods reviewed in this paper, including measuring vibration and roughness index, determining BLOS, and computing BI and BSI, all play a vital role in promoting public health. These methods encourage physical activity by promoting comfortable, safe, and attractive cycling environments. Moreover, prioritizing the health and well-being of cyclists contributes to an overall reduction in healthcare costs.

The developed assessment methods advocate for increased use of cycling and enjoyable cycling experiences [78]. The assessment methods usually suggest changes in the built environment; for example, cycling infrastructure provision aimed to improve the efficiency and safety of cycling [70]. In addition, cyclists' mental well-being is also a key consideration, as well-designed bicycle infrastructure can help reduce stress by separating cyclists from motorized vehicles [78]. City authorities worldwide have implemented various cycling infrastructures to promote bicycle use and minimize injury risk [79]. The developed tools for assessing bicycle infrastructure, such as BI, BSI, and BLOS, evaluate urban streets to identify problems on the urban streets and propose improvements [57,70,73]. Evidence indicates that implementing purpose-built bicycle-specific infrastructure facilities has a mitigating effect on crashes and injuries among cyclists.

It is worth noting that assessment methods also provide valuable suggestions for attracting more people to use the facilities. It is widely accepted that safe and comfortable infrastructure is critical to attracting more people to cycle [55]. The methods that have been developed have effectively achieved the goal by identifying the solution for the infrastructure. For example, Arellana et al. provided a BI tool for urban and transport planners to prioritize bicycle infrastructure projects [25]. Similarly, the BSI tool developed by Asadi-Shekari et al. [70] determined the necessary bicycle infrastructure facilities to ensure a safe environment for bicyclists. Such suggestions are essential to prioritize the bicycle improvements project, attract more people to bicycling, and help achieve broader community goals such as safer communities, improved air quality, and mental and physical health.

Now, a very important question regarding the applicability of the four different methods is: Which method should be used when? Since each method has a different scope of assessment, its applicability largely depends on the specific objectives of the evaluation. For example, whether the focus is on infrastructure performance, cyclist safety, cyclist comfort, or overall bicycle friendliness. Methods like the vibration and roughness index may be more suitable for evaluating surface conditions and comfort. Studies show that the vibration induced from the pavement surface of the bicycle paths or lanes significantly reduces the bicyclist's comfort [29]. The studies in this scoping review have assessed comfort objectively measured using methods such as IRI or RMS [32,34]. While studies have also correlated it with the cyclists' subjective feelings, a strong correlation has been found [28]. It was identified that comfort can be assessed using advanced instrumented probe bicycles, which can be costly [80]. However, studies have also proposed alternative and low-cost methods, such as using smart bicycle lights [16]. Cyclist comfort is influenced mainly by the pavement type, i.e., asphalt, concrete, or cobblestone [29,39]. However, any pavement irregularities on bicycle paths or roads, such as potholes, bumps, cracks, and maintenance hole covers, can affect cyclists' comfort, which may change the proposed index. Also, additional attention is required related to the type of bicycle, riding styles, and rider weights, which can affect overall assessment

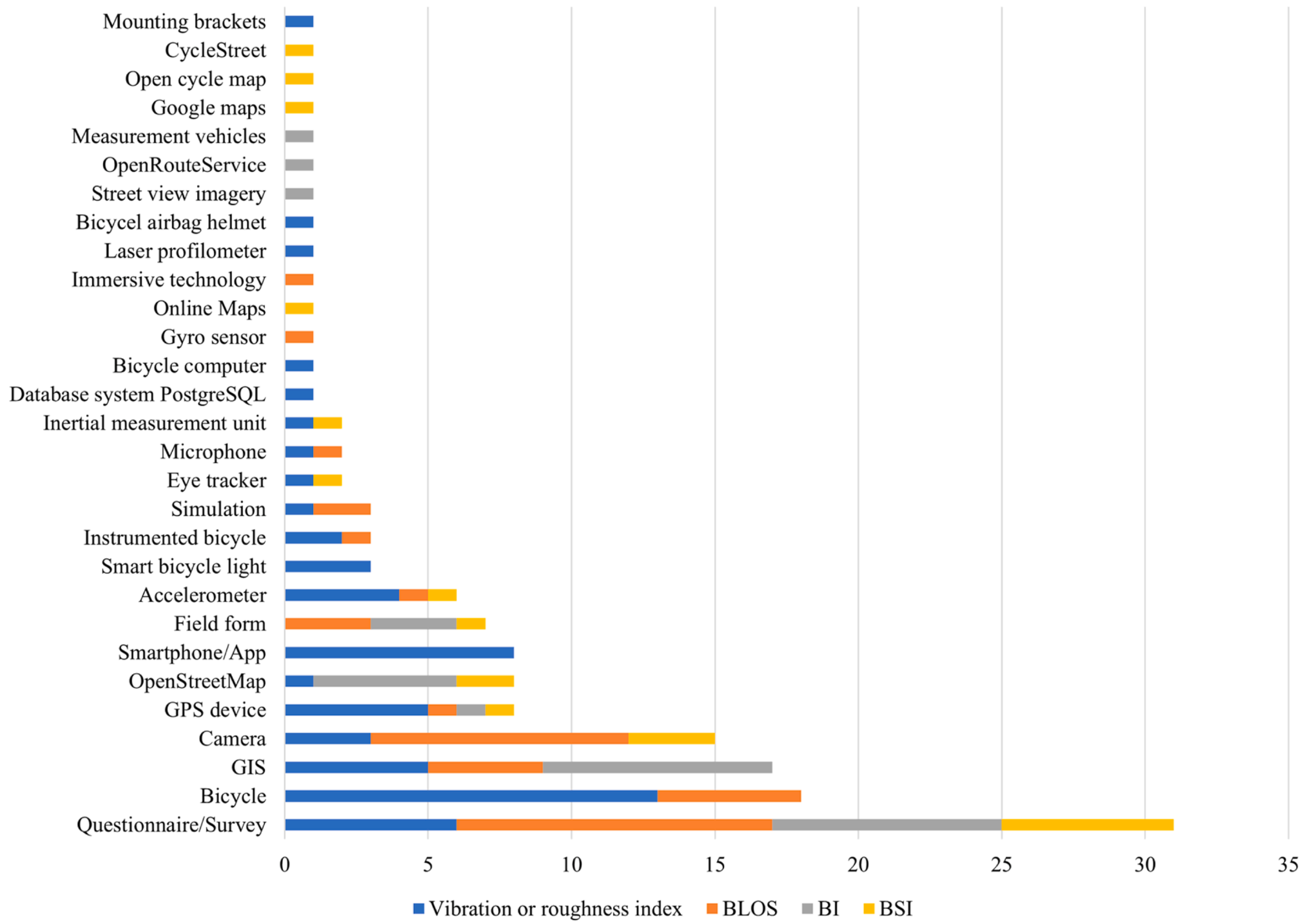

Fig. 4. Equipment and resources used in the evaluation methods for bicycle infrastructure.

[14,32].

The BLOS is particularly useful when evaluating the performance of specific components of a street or road, such as street segments or intersections [27]. The indices in the BLOS theme mainly assess the bicycle environment for cyclists' comfort and safety using a range of variables. The stress experienced by cyclists is crucial to understand on road networks. Some studies have mainly focused on this element and developed LTS models. This method is applicable when bicyclists travel on bike lanes without physical barriers and roads with sharrows or no bicycle infrastructure are present. The LTS is valuable for planners when creating maps highlighting high-stress routes as priorities for new infrastructure development [53]. It can also be used as information to guide cyclists toward safer paths. The compatibility of roads to accommodate bicycles is crucial to promoting bicycles as a sustainable mode of transport. The BCI effectively illustrates how traffic and roadway factors—such as curb lane width, number of curb lanes, bike lane width, traffic volume, speed, and roadside development affect cycling suitability [46]. There is an increasing use of video cameras in BLOS studies, as evidenced in the selected studies in the scoping review. Since BLOS also incorporates user perception, e.g. [44,46,49,52]. Some studies utilizes video footage to rate the segments or midblocks for the variables' importance later used in the development or assessment of BLOS. The technique proves effective, allowing for convenient ranking or perception assessments without compromising the accuracy of the study results.

Similarly, if the aim of the assessment is required for overall bicycle friendliness, methods under BI themes are particularly useful. They provide a comprehensive framework for analyzing and suggesting improvements in cycling infrastructure. Although the BIs are a handy tool for urban planners, they can be time-consuming considering the analysis of the urban bicycle networks [61]. However, the OSM data methods enable a semi-automated data collection to calculate indices, making it more efficient for analyzing extensive regions. OSM is considered a promising source, particularly due to its 'real-time' nature in contrast with static open data sources, and it contains detailed information for inventorying bicycle infrastructure [18,81]. Nevertheless, the information in OSM varies considerably by region; its utility depends on the geographic context, as demonstrated by Ferster et al. [81] in their study of six Canadian cities and Castañon et al. [18] in Póvoa de Varzim, Portugal. Some methods incorporate users' perceptions through questionnaires or expert inputs, which is important for having a subjective dimension. The perception enriches the evaluation by addressing cyclist needs and preferences. BI tool like BikeDNA is as open-source tool for reproducible quality assessment of bicycle infrastructure, but they can require extensive expertise to execute the method. One particular BI tool using ANP is an adjustable tool that can be easily adapted to a local context, for example, by removing criteria that are not applicable. This flexibility makes the tool highly relevant for diverse urban environments, allowing planners to tailor assessments to specific regions' unique needs and challenges, thereby enhancing its practical application. One particular BI method developed by Arellana et al. [25] is useful for its applicability in contexts where factors such as motorcycle traffic flow and the presence of police officers are significant, often seen in many developing countries. However, these indicators may not be as relevant in some European countries. Similar issues can be observed in certain European regions, such as southern European cities.

Nevertheless, the tool is useful for cycling infrastructure prioritization in the global south. The video data collection technique is claimed to provide results as reliable as those obtained through field studies [43].

The safety is considered as the most important element of bicycle infrastructure. The city governments worldwide are investing in bicycle infrastructure to attract more people to biking [23]. However, researchers have indicated that if cyclists do not feel safe, they are less likely to use the facilities [82]. The BSI primarily focuses on safety. Although the BLOS and BI consider safety aspects, they also consider other aspects. For example, BI considers factors such as comfort, bicycle attractiveness, cost of the trips (in some cases), coherence, and directness [25]. Hence, if the aim of the bicycle infrastructure assessment is only safety, the BSI methods are more applicable. The methods include direct field observations to measure traffic and infrastructure conditions and respondent-based questionnaires to understand cyclists' perceptions of safety. Previous research highlights the value of a combined objective-subjective safety assessment approach, as it effectively complements cycling safety evaluations by integrating measurable data with user perceptions, offering a more comprehensive understanding of safety [79]. Two BSI studies has incorporated weather conditions [73, 76], which can be particularly useful in applying the tool to similar weather conditions, i.e., snowy weather. The downside of some methods is their limited applicability beyond developing countries, as it is designed around the highly varied traffic flow conditions and average speeds typical of mid-sized cities in these regions. A point system can be very useful as it offers an easy-to-follow methodology. Asadi-Shekari et al. [70] suggested this method for street safety based on its alignment with recognized safety guidelines.

This review has a few limitations; firstly, this scoping review only considers the articles published in journals or conference papers published in proceedings. We did not consider grey literature, such as technical reports, policy briefs, government publications, and industry white papers in the analysis. Grey literature, such as policy briefs or government policies, often provides insights into practical applications and assessments of the applied work; we recommend them in future studies. In addition, this field of bicycle infrastructure is interdisciplinary, and this scoping review tried to group the studies based on the assessment commonalities. While searching the relevant articles using the search strings developed, we might have missed some articles, given the interdisciplinary scope of the field.

5. Conclusion

Bicycle infrastructure conditions strongly influence the perceived comfort and safety of cyclists. Different methods have been developed to assess the aspect of comfort and safety of the bicycle infrastructure. Understanding the scope of assessment methods is essential for evaluating bicycle infrastructure effectively. A clear knowledge of their objectives, limitations, and applicability ensures the selection of the most suitable method to address specific aspects of cycling facility evaluation and improvement. The assessment methods developed vary greatly in scope. Based on common characteristics, this scoping review categorized these methods into four groups (vibration index, BLOS, BI, and BSI).

Some developed methods are generalizable and adaptable; however, it is crucial to consider relevant methods when applying them. For example, the BI method is the most suitable approach when conducting an overall bicycle friendliness of a city because BI includes components like comfort, safety, attractiveness, cohesiveness, and cohesion of bicycle infrastructure. The vibration or roughness index is more appropriate for assessing the comfort levels of bicycle infrastructure, particularly concerning pavement conditions. This technique evaluates the smoothness of cycling routes, making it a pertinent choice for assessing comfort.

Similarly, the BSI index is relevant when assessing the safety of bicyclists on a given route. BSI incorporates a combination of objective data and user perceptions, making it a robust tool for evaluating and suggesting improvements in the safety aspects of bicycle infrastructure. Adapting the assessment method to specific needs ensures a thorough and targeted analysis, contributing to a more customized assessment. This scoping review provides a detailed overview of assessment methodologies, which will help city authorities select appropriate assessment methods tailored to specific contexts. Some methods require advanced technical skills for implementation, which is needed to enhance the accuracy of the findings. This review paper also guides the selection of appropriate methods by categorizing the required technical skills, estimated time, and associated costs from low to high. This information enables urban and transport planners to make informed decisions when choosing and applying the most suitable method for their needs. The availability of infrastructure data is essential for adapting assessment methods to specific contexts. The unavailability of data can significantly limit the range of methods that can be applied. For example, the comprehensive bicycle friendliness (bikeability) of an urban area or neighborhood assessment can be difficult and time-consuming without secondary data availability. However, some methods that utilize OSM data can provide an accessible and efficient alternative for such evaluations.

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CRediT authorship contribution statement

Tufail Ahmed: Writing – review & editing, Writing – original draft, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Ali Pirdavani:** Writing – review & editing, Validation, Supervision, Resources, Methodology, Formal analysis, Data curation, Conceptualization. **Irene Febryana Sitohang:** Writing – original draft, Visualization, Methodology, Formal analysis, Data curation. **Geert Wets:** Writing – review & editing, Validation, Supervision, Resources, Funding acquisition, Conceptualization. **Davy Janssens:** Writing – review & editing, Visualization, Supervision, Resources, Project administration, Methodology, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that there are no conflicts of interest.

Appendix 1

Studies in the relevant assessment category

	Vibration or roughness index	BLOS	BI	BSI
Studies in each theme	[14,16,28–41]	[11,26,42–55]	[25,18,56–60,62,63,65–69]	[23,70–77]
Count	16	16	14	9

Appendix 2

Web of Science: (TS=(“bicycle” OR “cycling” OR “bike”) AND TS=(“infrastructure” OR “facility” OR “lanes” OR “path”) AND TS=(“assessment” OR “evaluation”)).

Scopus: TITLE-ABS-KEY (“bicycle” OR “cycling” OR “bike”) AND TITLE-ABS-KEY (“infrastructure” OR “facility” OR “lanes” OR “path”) AND TITLE-ABS-KEY (“assessment” OR “evaluation”) AND PUBYEAR > 2003 AND PUBYEAR < 2026 AND (LIMIT-TO (DOCTYPE, “ar”) OR LIMIT-TO (DOCTYPE, “cp”)) AND (LIMIT-TO (LANGUAGE, “English”)).

Data availability

Data will be made available on request.

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