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Bicycle performance monitoring on a two-way protected cycle lane related to different separation elements

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Abstract
Although the use of bicycles is increasingly promoted and widespread across Europe, cyclist fatalities have remained stable since 2010, likely due to insufficient safe of the infrastructure. The study investigates bicycle performances and cyclist's safety in urban context to assess which factors influence the perception of the users. Employing an instrumented bike with advanced sensors and eye-tracking device, the effects of environmental and infrastructural factors were assessed. Conducted in Florence, Italy, the research collected data from 20 participants on a 1.2 km route divided into sections with varying separation types, including curbs, vegetation, barriers, and parking zones. The safety assessment was realized comparing speed with participants' fixation patterns, declared safety, infrastructural elements and vehicular flows across cycle sections. The accelerometer data quantified pavement-induced vibrations, categorizing comfort levels per ISO standards, and highlighting bicycle performance in riding comfort. Statistical analysis, including ANOVA and correlation assessments, identified that duration of fixations in the front area ($r = 0.469$, $p < 0.001$) and declared safety perception ($r = -0{,}449$, $p < 0.001$) most influence the speed in the analyzed cycle section. These findings lead to reveal information on the impacts of cycle infrastructure on safety perception and users behavior. This research underscores the necessity for human-centered design in cycling infrastructure to enhance urban cyclists' safety and comfort.

Keywords Cycle safety, Instrumented bicycle, Eye tracker, Visual attention

1 Introduction

Cycling is a transport mode which increasing in popularity, particularly in urban areas and in cities where bicycles offer a sustainable and healthy alternative to private cars [1]. This transport mode is recognized as a low-cost, low-emission mode of transport [2] that not only fills gaps in existing transport systems, in last mile transportation as well, but also contributes significantly to public health and mental wellbeing [3–5].The release of the EU Urban Mobility Framework [6] represented a major shift in the prioritization of cycling within urban transportation systems in Europe. For the first time, the EU Commission has placed a strong emphasis on cycling and other active modes of transport in a crucial policy document [7]. Local governments have made significant efforts to promote cycling through policy initiatives. However, merely encouraging cycling without enhancing infrastructure poses significant safety risks. Despite the evident benefits, the issue of cyclist safety is a critical concern in urban transportation planning, particularly as cycling grows in popularity. According to the European Commission [8] Facts and Figures Cyclists since 2010, cyclists are the only category of road users for which there has been no decline in fatalities. Cyclist fatalities have fluctuated between 1800 and 2100 annually since 2010. The increment in popularity of cyclability over the past decades, together with insufficient investment in safe cycling infrastructure may partly explain the stagnation in cyclist fatality rates. As the overall number of road fatalities has decreased by 34% since 2011, the proportion of cyclist fatalities within total road deaths has risen from 7% in 2011 to 10% in 2020. Regarding location, most cyclist fatalities occurred on urban roads (57%, compared to 40% for all road deaths). Compared to total road fatalities, a smaller proportion of cyclist deaths occurred on road stretches (67% versus 80%), while a higher proportion occurred at junctions (16% versus 9%) ("European Commission [8] Facts and Figures Cyclists. European Road Safety Observatory. Brussels, European Commission, Directorate General for Transport.," n.d.). Cyclists are often forced to share roads with motor vehicles, which increases the likelihood of accidents [9], particularly in high-traffic areas. Apart from the number of fatalities, cycling is often perceived as unsafe and stressful, largely due to the risks posed by motor vehicles, high traffic speeds, and poorly designed or inadequately maintained cycling infrastructure [10, 11]. The subjective user experience which lead to a perceptions of danger and discomfort deter potential cyclists, may reduce the effectiveness of cycling promotion strategies in urban areas. The general consensus is that where cycling is perceived as "safer", interest in cycling will increase [12]. Research indicates that cyclists, especially women and older individuals, express strong preferences for infrastructure that separates them from motor traffic, emphasizing the importance of creating dedicated cycling lanes to reduce stress, improve safety end enhance equity [13, 14]. Without substantial improvements to cycling infrastructure, increasing the number of cyclists alone will encounter the underlying safety issues. In addition to the dangers posed by motor traffic, pavement conditions are a significant factor in determining cyclists' safety and comfort. Well-maintained cycle paths and cycle lanes will help promote cycling [15], as this impacts the safety, accessibility and riding comfort [16, 17]. Studies have shown that pavement issues, such as potholes, debris, and uneven surfaces, are key stressors for cyclists, influencing both their perception of safety and their behaviour on the road [18]. This suggests that the road surface condition affects the willingness to cycle [19–22]. Despite being essential for cyclists' comfort, maintenance of these facilities is often inconsistent, and the infrastructure suffers from a lack of proper assessment. Addressing these deficiencies is crucial, particularly as the demand for cycling continues to rise in urban areas. For instance, quantitative studies using GPS data and surveys have provided valuable insights into cyclists' route preferences, helping to identify the infrastructural characteristics that make routes more attractive [23, 24]. However, these studies often fail to explain the deeper motivations behind cyclists' route choices or how specific infrastructural factors affect their perception of safety. This gap in the literature underscores the need for more qualitative research that explores how cyclists perceive and evaluate existing infrastructure. Understanding these perceptions is essential for creating cycling routes that are not only functionally effective but also perceived as safe by users. To address this gap, there is growing interest in developing tools that combine real-time feedback on both infrastructural and behavioural factors. Such a tool for infrastructural monitoring could be integrated directly into bicycles, providing continuous data on the condition of cycling infrastructure and offering insights into how cyclists respond to various road conditions and traffic interactions [25, 26]. In addition, continuous, real-time physiological measurements of riders' subjective experiences also have the potential to inform bike riding policy and practice [27]. This would allow for a more accurate assessment of the actual safety of cycling sections, as opposed to relying solely on perceived safety. Cyclists encounter various external stimuli while undertake a cycle ride experience (i.e. motor vehicles, pedestrians, potholes, and other potential safety hazards) and mobile eye tracking devices are powerful tools for capturing cyclists' vision during in site experiments. Mobile eye tracking provides insight into which environmental features cyclists focus on while riding [28–30]. Cyclists' perceptions of safety and comfort (PSC) significantly impact travel satisfaction and are crucial for evaluating low-stress cycling facilities. Traditional methods of measuring PSC, such as stated preference (SP) and revealed preference (RP) surveys, are prone to biases and limitations in data resolution [31, 32]. Eye tracking offers an objective, high-resolution alternative for assessing cyclists' stress levels in real-time. Eye tracking devices provide data on what cyclists focus on, which can be correlated with biomarkers such as galvanic skin response and heart rate to measure emotions like stress. Visual cues often trigger emotional responses, and observing how individuals look at objects in their surroundings helps interpret these emotions [33, 34]. Understanding the different types of oculomotor events and their functions is essential for interpreting eye-tracking data. In cycling behaviour studies, gaze records are often used as indicators of cognition, attention, and vigilance [35]. According to [36], fixation in terms of number and duration, saccades, and are the only eye movements that can infer overt visual attention.. Researchers employ fixation frequency data to investigate variations in visual processing strategies among participants and to evaluate differences across experimental conditions [37–39]. Furthermore, research has utilized fixation frequency metrics to elucidate diverse visual search patterns and establish correlations between hazard perception and visual processing tasks [40, 41]. Indeed, navigating at velocities that constitute an intermediate range between ambulatory locomotion and vehicular transport, cyclists manifest a horizontal visual field amplitude that is situated within the spectrum defined by the expansive perceptual range of pedestrians and the comparatively circumscribed field of motor vehicles [39]. Usually, unrestricted vertical field of view, are focused on the monitoring road quality [42]. Added to this, however, cyclists frequently negotiate shared roadway environments with motorized vehicles, necessitating enhanced vigilance toward traffic dynamics and potential hazards[43]. Consequently, empirical findings regarding visual behavior patterns observed in other road users cannot be directly extrapolated without eye tracking devices. The implementation of mobile eye-tracking methodologies in naturalistic cycling investigations represents an emerging experimental approach, with pioneering research initiatives originating in Belgium [40]. Over the past decade, more studies have employed diverse samples and research objectives. Selecting and interpreting gaze metrics is critical for understanding cyclist behaviour and perception. Multidisciplinary approaches to cycling research have incorporated diverse measurement methodologies, extending across domains such as infrastructure impact assessment, human–computer interaction studies, and psychological examinations [44]. The present research endeavors to elucidate the relationship between cycling infrastructure sections and resultant users behavior, examining how diverse path characteristics influence rider performance. Specifically, this investigation defined bicycle performance in terms of speed and comfort, the latter calculated through vertical accelerations measured at the seat. These performance indicators were then related to cycle path typologies, fixation patterns and data from a dedicated survey, enabling a comprehensive analysis of the correlated parameters (Fig. 1).

2 Materials and methods

2.1 Cyclists selection and sensors

A total of 20 participants (71% males–29% female) with a range between 31–60 years old (43% 31–40 years, 38% 41–50, 19% 51–60) took part in this experiment. Notably, none of the participants wore eyeglasses. Participation in the experiment was entirely voluntary, and the University of Bologna approved the protocol. The participants were blinded to the true objectives of the study. The cycling habits of the participants reveal that the majority, 62%, rarely used a bicycle, indicating a predominantly infrequent engagement with cycling. In contrast, 33% of the participants reported daily bicycle use, highlighting a smaller group with consistent cycling habits. A minimal proportion, only 5%, cycled two days per week. Regarding the distances travelled, 60% of the participants typically cycled distances of 5 kms or more, demonstrating a tendency towards longer trips among the majority. A smaller subset, 20%, cycled between 3 and 5 kms, while an equal proportion, 20%, cycled distances between 1 and 3 kms. No participants reported cycling distances of 1 kms or less, suggesting that most individuals who engaged in cycling tended to cover moderate to long distances. These findings indicate a diverse range of cycling habits within the participant group, with infrequent cycling predominating but a significant proportion of longer-distance cyclists.

The study involves two specific devices: an instrumented bicycle and a mobile eye-tracking system. The mobile eye tracker used is the Tobii Pro Glasses 3 (Fig. 1), designed

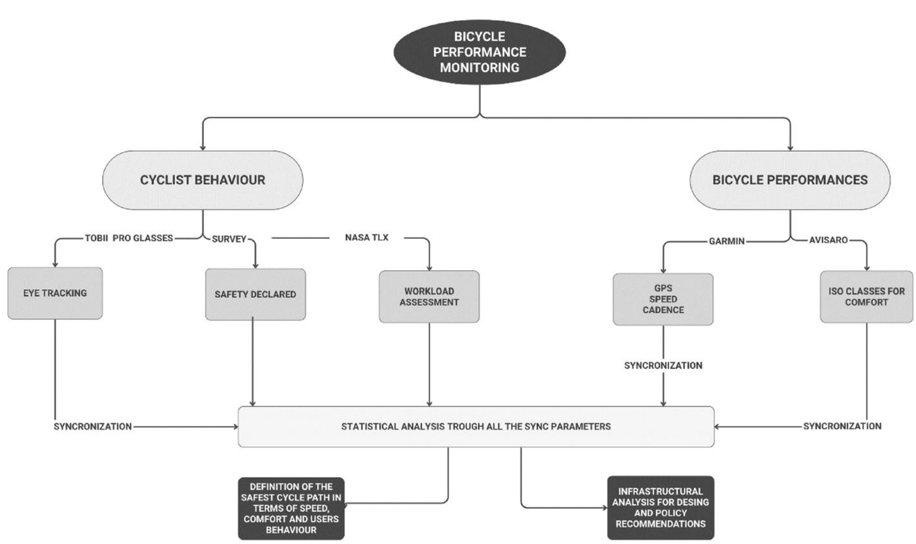

Fig. 1 Methodology and goal assessment of the research

to capture the participant’s gaze during the experiment. It is a wearable system capable of capturing eye movement data with high spatial precision and can sample data at 50 Hz and a scene camera with a 106° field of view. The bicycle used in the experiment was a city bike (called Almabike) equipped with several sensors and devices strategically installed on the front and rear sections of the bicycle to capture relevant data:

- Garmin Edge 130 Plus: A device with an integrated positioning system that was used to store kinematic data with a sampling frequency equal to 1 Hz;
- Avisaro Inertial Measurement Unit (IMU): a data logger with 6 DOF IMU units (3 axis acceleration/3 axis gyro) fixed on the rear seat to measure the accelerations with a sampling rate that was set to 100 Hz;
- Cadence and Speed Sensor: To monitor the cyclist's pedaling rate. It communicates through ANT + transmission to the Edge 130 Plus with a sampling frequency equal to 1 Hz

Each of these components played a critical role in collecting comprehensive data during the experiment, ensuring a detailed analysis of both the participant's physical performance and the external environmental conditions. To align data streams recorded from devices operating at different sampling, a common event-based synchronization method was adopted. Specifically, a distinct and simultaneous physical stimulus, observable across all recording systems, was used as a temporal marker. In details a tap on the bicycle seat was used as a synchronization marker across devices. This event produced a distinct spike in the accelerometer signal that was visually detected from the eye-tracking video, enabling temporal alignment using the timestamp across the devices.

2.2 Experimental methods

A 1.2 km cycling route was selected in Florence, Italy, encompassing both training and actual test segments. The training routes were incorporated at the beginning of the experiment and interspersed between the actual test routes to help participants acclimate to road conditions, thus facilitating the observation of their natural gaze behavior during the main portions of the study. Cyclists' gaze behavior was not analyzed while they were riding on the training routes. The cycling routes were divided into four sections, homogeneous by carriageway separation type. This can be visible in Fig. 2.

All the different sections consist of protected bi-directional cycle paths at street level, separated with curbs to a raised pedestrian path on the right. The width of the cycle paths over the different sections can be considered uniform and coherent with the regulation. Table 1 summarizes the main characteristics of the different sections and defines

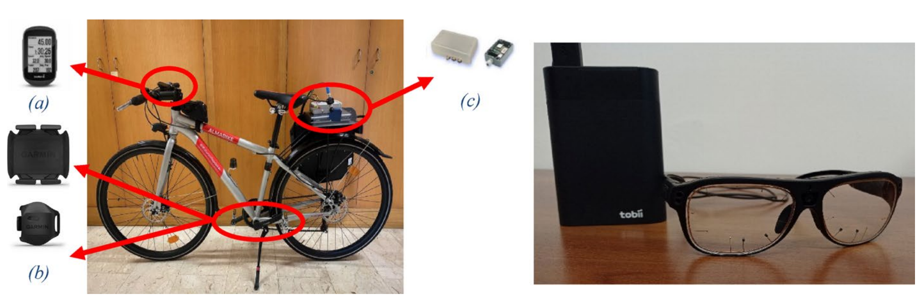

Fig. 2 Left: alma instrumented bike: Garmin edge 130 plus (**a**); cadence sensors (**b**); IMU accelerometer (**c**) Right: Tobii pro glasses 3

Table 1 Cycle paths characteristics and type of separation element

Section ID	Section	Separation element with the carriageway (left)	Length (m)
S1_Curb	1	Curbs	300
S2_Green	2	Vegetation	200
S3_NJ	3	New Jersey Barriers	100
S4_Park	4	Curbs + Parking	300

Fig. 3 Cycling routes subdivision into S1_Curb, S2_Green, S3_NJ, S4_Park (source: Google Earth©)

the type of cycle path separation according to M.D. n. 557 del 30/11/1999 art. 4 and R.l. n. 10/2017.

S1_Curb and S2_Green cover different portions of Viale Lavagnini, both featuring protected cycle paths characterized with red-coloured surfaces (Fig. 3). These paths are physically separated from the raised sidewalk and road by curbs (S1_Curb) or urban greenery (S2_Green). S3_NJ is in the first section of Viale Matteotti, it is physically divided from the vehicular carriageway by New-Jersey barriers and on the other side is separated from the raised sidewalk by curbs. Finally, S4_Park, also located along Viale Matteotti, consists of a protected red cycle path with physical separation from the raised sidewalk by curbs and parking lots on the other side. The experiment was conducted on two different days from June 13 to 14, 2024. A calibration procedure was performed for each participant to ensure the accuracy of the eye movement recordings. Before the test, participants received a brief description of the path to be followed, the equipment to be worn during the experiment, and its operation. It was asked to cycle as they commonly do, to interfere as little as possible with their cycling behaviour. All participants rode the same bicycle for an equal cycling condition and the experiment lasted for approximately 10–15 min. Questionnaires were administered at the end of the session, specifically asking participants to target two main different information. The first one aims to collect demographic and personal data (e.g., age, gender, driving experience, comfort during the ride). The second one wants to collect cognitive load during the test. For this reason, a NASA Task Load Index was used to profile users and their perceptions. In addition, a declaration of the perceived safety was asked of each one.

3 Results

A dedicated questionnaire was developed to assess the declared level of safety, the comfort with the instrumented bicycle and the workload associated with the assigned task. It is observed that 90% of the participants did not report any discomfort while wearing the previously described equipment. For analyzing the cyclist effort during the ride, a NASA TLX was realized after the test. Following the standard procedure, each participant first rated six workload subscales on a 0–100 scale. Subsequently, participants completed 15 pairwise comparisons between the subscales to determine the relative weight of each dimension (for a maximum weight of 5 for each subscales). These weights were used to compute a weighted workload score for each individual. Final results were aggregated across participants based on these individually weighted scores. The NASA-TLX test indicate that mental and temporal demands were the most significant contributors to perceived workload, with both dimensions exceeding 25%. Physical demand scored lower (22%), suggesting it was not a predominant factor. Performance, effort, and frustration levels were moderate (less than 20%), highlighting a balanced but cognitively challenging task environment (Fig. 4). However, the reported task-related exertion levels were minimal and appeared to have no significant impact on the test realization.

Moreover, the participant declare their safety perception during the route using a Likert scale from 1 (I feel totally safe) to 5 (I perceive constantly the danger). The declared safety rating was aggregated divided for the dangerous rank (with a 4 or 5 as a grade) and the safe perception (from 1 to 3). The results (Fig. 5) indicate that 90% of the participants reported high safety levels across sections S1_Curb, S2_Green, and S4_Park. Conversely, Section S3_NJ exhibited the greatest danger perception (30%).

The analysis of 20 participants' data coming from the different sensors and tools was carried out. First of all, the speed was extracted from Garmin Sensors and divided per section using GPS position through GIS software. Table 2 defines the main characteristics of the different sections along the tested route. In the analysis of the speed data, the stops and the zero were deleted from the calculation.

The average speed of sections S2_Green, separate cycle path (18,62 km/h), and S3_NJ protected cycle path (12,02 km/h) are respectively the highest and the lowest. A decrease in speed is evident in the shift to the protected cycle section. Standard deviations show low variability of speed data between different configurations.

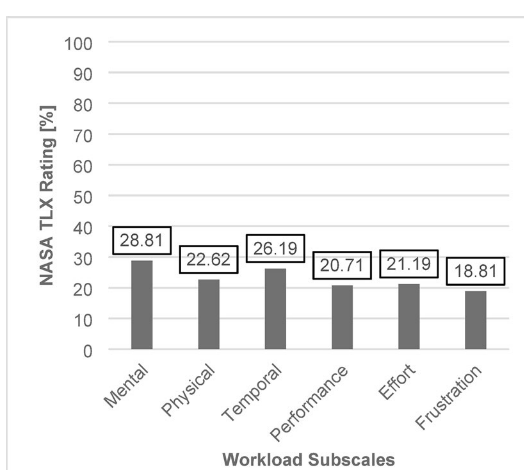

Fig. 4 Nasa TLX results

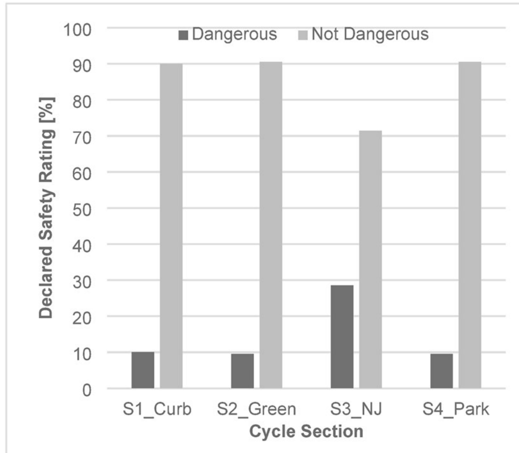

Fig. 5 Declared Safety Perception on the section

Table 2 Descriptive statistics for speed of the sections

Section ID	Average	Standard	Minimum	Maximum
S1_Curb	14.94	1.78	12.12	18.62
S2_Green	15.58	1.50	12.88	18.98
S3_NJ	12.02	1.35	8.71	14.49
S4_Park	12.94	1.19	10.13	15.40

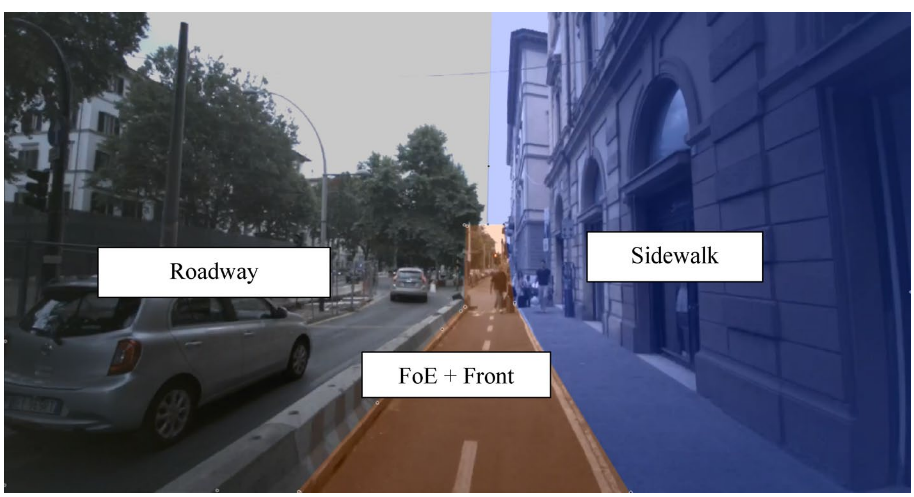

Fig. 6 AOI analysis from Tobii mobile eye tracker

Moving to the gaze data, they were extracted from the device, using Tobii Pro Lab software for the analysis It allows for the creation of AOIs that dynamically follow the cyclist's gaze. Additionally, the timestamp associated with each section serves as a marker for segmenting the route, taking into account the GPS location. All the evaluated recordings maintain a gaze sample percentage over the threshold fixed to 85% [38]. To reduce potential subjectivity during the frame by frame analysis the following areas of interest (AOI) [30, 42], typically used in literature, were defined: Roadway nereby, Sidewalk, Focus of Expansion (FoE) and front direction (Fig. 6). In this way the subjectivity was minimized by not labelling objects, but dividing the visual scene in the three main region of the cyclist view.

For each area, the duration and the number of fixations were extracted (Fig. 7) in order to understand possible relation with the cycle kinematic parameters. In particular two different main metrics were examined from the video analysis (Tobii [45]):

- The fixation, defined as the sequence of raw gaze points, where the estimated velocity is below the velocity threshold set in the I-VT gaze filter (30°/s).
- The Fixation Duration that is the time between the first gaze point and the last gaze point in the sequence of gaze points that makes up the fixation greater than 60 ms.

Due to the different length of the cycle section, the percentage of these two-gaze data was analyzed. The most fixed AOI is the front one both in term of distribution and counts, especially for section S4_Park. Analyzing the AOIs in the sides, the section S1_curb and S3_NJ record the most fixation and duration. In particular section S1_curb, it records the higher number of distraction than the front direction. In detail, the road is more perceived in section S3_NJ than in the others, the sidewalk captures more fixation in section S1_curb. Section S2_green records the lowest value of fixation in the road direction, due to presence of vegetation. Further investigation using statistical analysis will be defined in the next paragraph.

Moving to the accelerometer data, a MATLAB code was realized to perform an algorithm that red the accelerometer data. A high-pass filter was applied to the vertical acceleration signal to remove low-frequency components, isolating the higher-frequency oscillations. The synchronization process through a physical stimulus, as described before (Par 2.1) was used as a temporal marker. to align them with GPS records. Subsequently, the root mean square (RMS) value per second was calculated. The following equation was used for the RMS calculation, where N acceleration value and xi is the value for vertical acceleration:

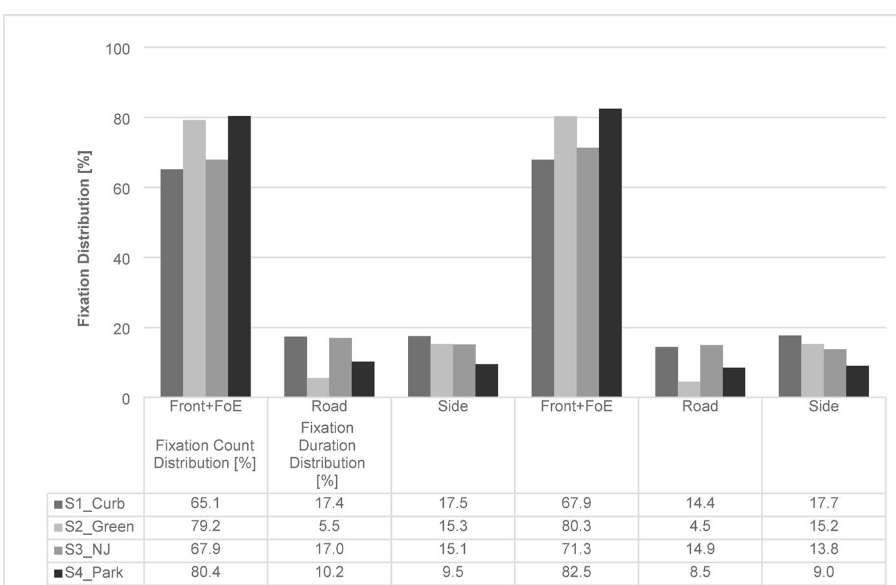

Fig. 7 Percentage distribution of eye tracking data (duration and number of fixation)

Table 3 Comfort perceptions for different vibration levels

Acceptable values of vibration magnitude for comfort (RMS m/s^2)	Likely user's reaction	Category
< ±0.315	Not uncomfortable	A
±0.315 ÷ ±0.63	A little uncomfortable	B
±0.5 ÷ ±1	Fairly uncomfortable	C
±0.8 ÷ ±1.6	Uncomfortable	D
±1.25 ÷ ±2.5	Very uncomfortable	E
> ±2.5	Extremely uncomfortable	F

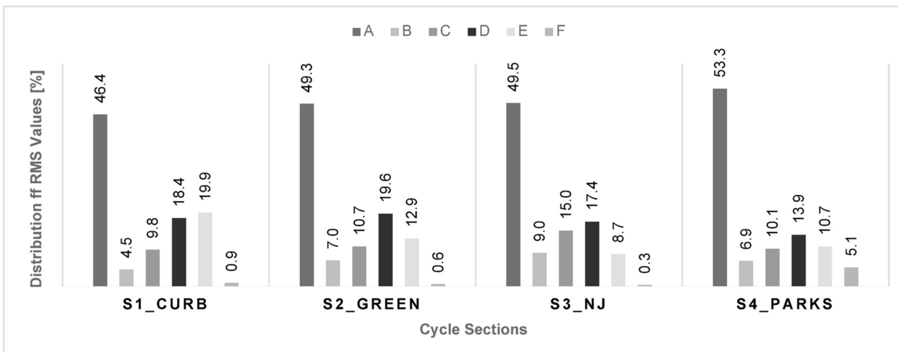

Fig. 8 Distribution of RMS into ISO classes for the different sections

$$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2} \quad (1)$$

The classification of these values according to Table 3, adopted from ISO 2631-1, was carried out. This clause concerns the estimation of the effect of vibration on the comfort of persons in normal health who exposed to whole-body periodic, random and transient vibration during travel, at work or during leisure activities ("UNI ISO 2631–1—Mechanical vibration and shock —Evaluation of human exposure to wholebody vibration—Part 1: General Requirements [46]). To realize it, vertical accelerations for each section were calculated using the output from the sensors, converting them in m/s^2, filtrated for noise, and categorized between the different ISO classes.

Dividing the data, according to the aforementioned regulation, yields the percentage distribution for each section (Fig. 8). The distribution of comfort levels varies significantly between sections, indicating that different sections of the cycling pavement provide varying degrees of vibration comfort.

Section S1_curb has a relatively higher proportion of points (40%) classified under lower comfort, Class D), whereas Section S4_parks demonstrates a more balanced distribution among classes C, D, and E. In another hand, section S3_NJ show the most comfortable path with 74% of vibration values with low level of discomfort. In the end, the chart underscores the variability in vibration comfort across the cycling pavement sections, suggesting differing pavement conditions or maintenance standards that influence the overall comfort experienced by cyclists.

3.1 Statistical analysis

Differences from the variables, especially speed and fixation across the different section, were investigated using ANOVA test with significance level set at $p \le 0.05$. In addition,

Table 4 Single-way ANOVA between the speed sections

ANOVA	Sum of squares	df	Mean square	F	Sig
Between Groups	319.908	4	79.977	30.655	0.000
Within groups	247.851	95	2609		
Total	567.760	99			

Table 5 Turkey post hoc

(I) Sections	(J) Sections	Mean differences (I–J)	Std. error	Sig	95% Confidence interval	
					Lower bound	Upper bound
S1_Curb	S2_green	− 1.379	0.511	0.061	− 2.799	0.041
	S3_NJ	2.638*	0.511	0.000	1.218	4.059
	S4_Park	0.637	0.511	0.724	− 0.783	2.057
S2_green	S1_Curb	1.379	0.511	0.061	− 0.041	2.799
	S3_NJ	4.017*	0.511	0.000	2.597	5.438
	S4_Park	2.016*	0.511	0.001	0.596	3.436
S3_NJ	S1_Curb	− 2.638*	0.511	0.000	− 4.059	− 1.218
	S2_green	− 4.017*	0.511	0.000	− 5.438	− 2.597
	S4_Park	− 2.001*	0.511	0.002	− 3.422	− 0.581
S4_Park	S1_Curb	− 0.637	0.511	0.724	− 2.057	0.783
	S2_green	− 2.016*	0.511	0.001	− 3.436	− 0.596
	S3_NJ	2.001*	0.511	0.002	0.581	3.422

*$p < 0.005$

the linear correlation between all the factors, after the synchronization process using timestamp from different sensors, and speed has been outlined. First of all, the normality test of Shapiro Wilk and the Levene test for the variance similarity assessed that the speed values are quite normally distribute for each section. It can be confirmed by the statistical tests, the speed values are distributed according to a normal distribution and have comparable variances ($p > 0.05$). Subsequently, a one-way ANOVA was performed in order to understand if there are some statistical difference between the mean values of velocity from the different sections (Table 4).

Results of the ANOVA showed a significant difference between the speed of the four sections ($F(4,95) = 30{,}655$, $p < 0.001$). So, the null hypothesis that the difference between the average values is equal to zero would be rejected. For investigating further, the correlation between the different cycle sections, in terms of speed, a Turkey post hoc analysis (Table 5) was carried out.

The section S2_green (M = 15.58, SD = 1.50), where the mean speed is the highest, showed relevant differences with almost all the other ones, not for section S1_curb (M = 14.94, SD = 1.78) probably due to the similarity of the geometric characteristics. Indeed, the section S4_ (M = 12.94, SD = 1.19), the slowest in the test, show significant differences between all the speed sections. It suggests that the difference in the mean value of speed changes according to several factors, such as road elements, users or fixations. The time alignment based on the handlebar tap, as a synchronization marker, gives the possibility to analyze correlation between each sensors. In particular to understand which factors influence the speed along the cycle route, several elements, for each cycle route, was extracted from the video recordings and the survey analysis:

- Fixations in terms of duration and count of the cyclist gaze;
- ISO Comfort classes;
- Declared safety of the participant;

- Number of the cyclist encountered along the way (both in the same and opposite direction);

Therefore a further investigation on what influences the speed of the cyclist, has been outlined below. Studying the linear correlation between the parameters defined before, using Pearson's correlation matrix, it was possible to obtain the results in the Table 6.

The correlation analysis reveals that speed is significantly and positive correlated with the duration of fixations in the front area ($r = 0.469$, $p < 0.001$), the number of frontal fixations ($r = 0.322$, $p < 0.001$), ($r = -0{,}449$, $p < 0.001$), and the number of cyclists encountered ($r = 0.299$, $p < 0.001$). These results suggest that increased attention toward the front visual field may facilitate higher cycling speeds. Conversely, speed tends to decrease linearly with the worsening of pavement quality, as indicated by the ISO class ($r = 0.449$, $p < 0.001$), and with higher levels of perceived risk reported in the survey ($r = 0.359$, $p < 0.001$). Therefore, reduced speed appears to be influenced by both lower perceived safety due to the surrounding environment and pavement conditions, which are associated lower comfort levels. Probably the positive correlation with the encountered cyclist is due to the willing of overpassing. These results take into account the synchronisation between the eye tracker and the accelerometer, making the variables within the correlation matrix comparable.

To ensure the appropriateness of including these predictors in a regression model, multicollinearity was assessed using both Variance Inflation Factor (VIF) and collinearity diagnostics. All VIF values were well below the critical threshold of 4, with the highest being 1.607 for path quality. This threshold is consistent with commonly accepted methodological standards [47]. Similarly, condition indices remained below 12, and although the variables Frontal Fixation Duration and ISO Classes shared more than 60% of their variance in the same component, this redundancy was not sufficient to raise concerns about collinearity or model instability. In addition, a multiple linear regression model (MLR) was then constructed including the four predictors: fixation duration in the front area, path surface quality, perceived safety, and number of cyclists encountered. The model explained 31.8% of the variance in speed ($R^2 = 0.318$) indicating moderate explanatory power. The standard error of the estimate was 2.02, and the Durbin-Watson statistic was 1.414, suggesting a mild positive autocorrelation of residuals, though not problematic. These results confirm that the selected parameters and environmental factors jointly and meaningfully contribute to variations in cycling speed, without multicollinearity bias. The correlation patterns and regression model suggest meaningful relationships between parameters but further data collection would enhance the robustness of the model.

In conclusion, taking into consideration the fixations during the ride, ANOVA for the percentage of fixation in the three different AOIs was applied. This enhances the possibility to investigate which environmental factors catches the attention of the participant in the different cycle section. It was possible to assess if the presence or not of the curbs, road elements nearby and vehicle flow influence the speed of the participant. Firstly, it was investigated which are the distribution between sidewalk and road nearby, during the ride (as shown in Fig. 7). It is possible to emphasize that the quickest section S2_green show the largest number of lateral fixation and duration on the sidewalk, due also to the presence of vegetation in the other side, that closes the sight. On the other hand, the slowest one, S3_NJ, has more fixation oriented to the roadway, probably due to the

Table 6 Pearson correlation matrix

Pearson Correlation	Speed	Duration of fix			Fixation count			ISO classes for vibration	N° of Opp. cyclist	N° of encount. cyclist	Declared safety
		Front	Road	Side	Front	Road	Side				
Speed	1.000	0.469**	0.022	0.222*	0.322**	0.107	0.102	−0.449*	0.299**	0.167	−0.359**
ISO classes for vibration	0.449**	−0.570**	−0.229**	−0.221	−0.425**	−0.241	−0.117	10.000	−0.400**	−0.225	0.319
Declared safety	−0.359**	−0.218	−0.229**	−0.221	−0.425**	−0.241	−00.117	−0.319**	−0.178	−0.111	1.000

*$p < 0.005$ and **$p < 0.001$

presence of high vehicular flow. A single way ANOVA was performed to find statistical evidence based on the different cycle sections. Results of the ANOVA analysis (Table 7) showed a significant difference between the road ($F(4,95) = 8,463$, $p < 0.001$) fixations in the four sections. There were no significant differences between sections for the duration of sidewalk and frontal fixations, suggesting that the duration of fixations on the lateral and frontal area is similar between all sections considered.

For investigating further the correlation between the different duration of the fixation on road, a Turkey post hoc analysis (Tab. 8) was carried out.

Table 8 shows that section S2_green has significant differences from section S1_curb and S3_NJ, with a lower percentage duration of fixations on the road with differences of approximately 10 percentage units, respectively ($p \leq 0.002$). This indicates that in sections S2_green, and S4_parks, participants tend to fixate less on the road than in section S3_NJ, which is similar to the visual behaviour associated with section S1_curb. These findings suggest that road configurations where vehicular traffic is within users' visual field (sections S1_curb and S3_NJ) appear to influence both visual perception and speed choice behaviours.

4 Discussion

This study presents the analysis of two-days test where 20 participants cycle along a selected route with different sections using an instrumented bicycle. Data related to visual perception, acceleration and speed were collected. The participants were unaware of the study's purpose and confirmed that the instrumentation did not interfere with their cycling experience (90% of the sample). The test lasted approximately 15 min, including equipment calibration and route explanation. The selection of the cycle sections was conducted by choosing the same type of bicycle paths but varying surrounding road elements. To evaluate how these street elements affected cyclist safety, velocities and fixations were analysed across different sections in relation to the collected data (acceleration, interference, vehicle flows etc.) [48].

The analysis of the empirical data reveals several significant patterns regarding cycling behavior and visual attention across different infrastructure sections. The speed analysis demonstrates significant variations in cycling speeds. The separate cycle path (S2_green) exhibiting the highest mean velocity (18.62 km/h), while the protected cycle path with barrier (S3_NJ) recorded the lowest one (12.02 km/h). The decrease in speed during transitions to cycle sections suggests a potential correlation between infrastructure type and user behavior. The relatively low standard deviations across configurations indicate consistent speed patterns among participants.

For assessing it, eye-tracking data, were analyzed. Through Tobii Pro Lab software, sight data maintained robust reliability with gaze sample percentages (> 85%). %). Analysis of AOI reveals a predominant forward-facing gaze pattern across all sections [40, 49, 50]. However, Sections S1_curb, S2_green and S3_NJ demonstrated significantly higher lateral fixation frequencies and durations. Of particular interest, Section S1_curb exhibited the highest rate of visual attention deviation from the forward direction, with increased fixations on sidewalk features due probably to the high pedestrian flow. Section S3_NJ showed elevated road-focused attention compared to other segments (vehicles flow nearby), while Section S2_green reduced road fixation patterns appear attributable to the presence of green elements between cycle path and road. To analyze

Table 7 Single-way ANOVA between the fixation on different sections

ANOVA		Sum of squares	df	Mean Square	F	Sig
Frontal direction	Between groups	3124.160	4	781.040	3.978	.005
	Within groups	18,652.750	95	196.345		
Road direction	Between groups	2429.600	4	607.400	8.463	.000
	Within groups	6818.400	95	71.773		
Sidewalk direction	Between groups	882.700	4	220.675	1.873	.121
	Within groups	11,190.050	95	117.790		

Table 8 Turkey post hoc of duration of fixation on road

	(I) Sections	(J) Sections	Mean differences (I–J)	Std. error	Sig	95% Confidence interval	
						Lower bound	Lower bound
Duration of fixation on road	S1_Curb	S2_green	10.700*	2.679	.001	3.25	18.15
		S3_NJ	.250	2.679	1.000	− 7.20	7.70
		S4_Park	7.500*	2.679	.048	.05	14.95
	S2_green	S1_Curb	− 10.700*	2.679	.001	− 18.15	− 3.25
		S3_NJ	− 10.450*	2.679	.002	− 17.90	− 3.00
		S4_Park	− 3.200	2.679	.755	− 10.65	4.25
	S3_NJ	S1_Curb	− .250	2.679	1.000	− 7.70	7.20
		S2_green	10.450*	2.679	.002	3.00	17.90
		S4_Park	7.250	2.679	.060	− .20	14.70
	S4_Park	S1_Curb	− 7.500*	2.679	.048	− 14.95	− .05
		S2_green	3.200	2.679	.755	− 4.25	10.65
		S3_NJ	− 7.250	2.679	.060	− 14.70	.20

*$p < 0.005$

the relationship between all the recorded variables, the ANOVA, the correlation analysis and MLR between factors were carried out. Statistical analysis suggests that speed variations are influenced by the state of cycle, user safe perception and frontal attention. A positive correlation emerged between forward-focused attention and increased speeds, potentially indicating a relationship between perceived environmental safety and cycling behavior. In contrast, both perceived safety along the cycle paths and riding comfort—measured through vertical accelerations classified by ISO standards—negatively influence cycling speed.

The consistency in fixation durations between lateral and frontal areas across all sections suggests a uniform visual scanning pattern regardless of infrastructure type. The research suggests that the composition of the cycling environment significantly influences cyclists' visual scanning patterns. Specifically, in segments where vehicular flows are in close proximity to the cycle path—and thus within the cyclist's field of vision—there is a noticeable increase in attentional focus toward that side and a concurrent reduction in speed. Analyzing the correlation between traffic flow visibility and speed adaptation reveals a substantial perceptual-behavioral relationship in these cycling segments [39, 51]. These findings contribute to understand of how infrastructure design elements influence cycling behavior and perceived safety, with potential implications for urban bicycle infrastructure design and safety enhancement strategies.

5 Conclusion

The transition toward sustainable urban mobility systems heavily relies on encouraging non-motorized transportation methods, with cycling emerging as a crucial component [52]. Successful strategies promote multimodality, adjustments to the highway code that favour sustainable and active mobility, financial incentives for citizens to purchase and ride bicycles, and other actions that enable behaviour change [7]. Sustainable mobility has been growing, particularly in densely populated urban areas. For instance, recent data indicate a sharp increase in demand for cycling infrastructure, driven in part by the proliferation of electric micro-mobility options that have reduced travel times and physical exertion, with zero emissions [53]. Furthermore, the growing affordability of cargo bikes and the expansion of bike-sharing systems have significantly increased demand [54]. The rise in cycling adoption has been paralleled by a surge in dedicated infrastructure, supporting the expansion of this active transportation mode. Cumulatively, in 2023 for Italy, numerous incidents occurred involving bicycles (both electric and non-electric) and scooters, leading to hundreds of fatalities and thousands of injuries, including pedestrians who were struck [55]. An increase in fatalities has been noted among operators of scooters, bicycles, and electric bicycles, while the number has remained constant for pedestrians and decreased for other road users. This data underscores the evolving landscape of urban mobility and the concomitant safety challenges that arise with the adoption of new transportation technologies.

Urban planning often overlooks the user's perspective, deviating from a human-centered design approach. While surveys have been conducted to understand user experiences and opinions, they do not fully capture the actual experience of cycling on specific routes or segments. Consequently, various methods have emerged to study the cyclist behavior through advanced technological tools [39]. These include analyses of visual and cognitive perceptions using eye-tracking and performance assessments with GPS and other kinematic data [56, 57].

This research sought to combine these two areas, synchronizing available data, examined from the user and the vehicle, to evaluate the distinct cycling segments traversed. The present research aims to analyse, in terms of cycle safety, how the road elements during the ride, influence the kinematic and the behavioural actions of the cyclist. Despite its valuable contributions, this study has certain limitations. The sample size of 20 participants, while reflective of varied cycling habits, may not fully represent the broader population. Future studies with larger, demographically diverse participant pools could enhance the generalizability of the findings. Furthermore, the study's focus on a 1.2 km route in Florence might not capture the full scope of urban cycling experiences across different environments and distances. Expanding research to encompass varied geographic settings and infrastructure types would provide deeper insights into the influence of environmental factors on cyclist perceptions and behaviors. Additionally, while the use of a standardized instrumented bicycle ensured consistent data collection, it did not account for variations in personal bicycle setups, which can affect behavior and comfort. Nevertheless, the findings of this research contribute to move toward a user-centred approach for the design of cycling infrastructure. In particular, results confirm that infrastructural aspects, especially those related to pavement quality and safety perception, significantly influence both cyclists' perceptions and their performance. Therefore, incorporating both maintenance and safety perceptions into the planning process represents a crucial step toward safer and more comfortable cycling environments. Such an approach not only enhances perceived and actual safety but also plays a key role in encouraging cycling as a daily mode of transport, ultimately supporting modal shift away from environmentally unsustainable means. Future studies could consider equipping participants' personal bicycles with similar sensors, allowing for a more individualized understanding of cycling dynamics. Incorporating physiological measures, such as heart rate variability or skin conductance, alongside eye-tracking data, could offer a more comprehensive view of cyclists' stress and cognitive load in response to different infrastructure conditions. These future developments, supported by advancements in real-time data analytics and AI-driven behavioral modeling, could greatly expand our understanding of urban cycling. As cities work toward more active and sustainable mobility, these data-driven insights would enable more impactful infrastructure design, ultimately enhancing both safety and comfort for cyclists.

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Author contributions
Leonardo Cameli: Methodology, Software, Data curation, Writing—Original draft Riccardo Ceriani: Data curation, Writing-Original draft preparation, Software. Valeria Vignali: Supervision, Methodology, Investigation, Funding acquisition. Margherita Pazzini:, Formal analysis, Conceptualization, Writing—review & editing: Claudio Lantieri: Supervision, Validation, Software.

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Data availability
The data that support the findings of this research are not openly available due to reasons of sensitivity and are available from the corresponding author upon reasonable request. Data are located in controlled access data storage at University of Bologna.

Declarations

Ethics approval and consent to participate
This work involved human subjects or animals in its research. Approval of all ethical and experimental procedures and protocols was granted by the Bioethics Committee of the Alma Mater Studiorum - University of Bologna, Prot. n. 0048330. The authors declare that informed consent, through written agreements, was obtained from all individual participants included in the study, following a detailed explanation of the study's procedures, potential risks, and benefits.

Consent for publication
The authors declare that all the people involved give the consent to publish each individual and personal data.

Competing interests
The authors declare no competing interests.

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