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Visual Attention and Perceived Workload of E-Scooter Riders Across Selected Urban Route Conditions

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Abstract

Understanding how selected urban route conditions are associated with e-scooter riders' visual attention and perceived workload can support human-factor evaluation of micromobility environments. This study examines visual attention and perceived workload during real-world e-scooter riding across three selected urban routes in Zagreb with different infrastructure and traffic-environment characteristics. A field-based experimental methodology was used, integrating eye-tracking with post-ride perceived workload assessment through the National Aeronautics and Space Administration Task Load Index (NASA-TLX) questionnaire. Twenty-eight adults, predominantly novice or occasional e-scooter riders, completed the three selected routes. Visual attention and perceived workload were examined across the selected routes; because only one route represented each route condition, the findings are interpreted as route-level evidence rather than general infrastructure-type effects. One-way repeated-measures analyses of variance (ANOVAs) showed that route condition had a significant effect on mean fixation duration and on the weighted NASA-TLX workload score, indicating that riders' visual attention and perceived workload varied across the examined routes. To further examine these route-related differences, linear mixed-effects models were used as supporting analyses with participant ID as a random intercept. The results showed that R2 was associated with lower weighted workload than R1, while R3 was associated with higher weighted workload than R1. The route-complexity index was retained as an exploratory route-level descriptor rather than a validated continuous predictor. These findings highlight the importance of considering combined route, infrastructure, and traffic-environment characteristics when planning safer micromobility environments and developing appropriate regulations for e-scooter use. They also provide preliminary route-level human-factor evidence that can support future micromobility route evaluation and the development of human-centred guidance for infrastructure planning and e-scooter regulation.

Keywords: e-scooter riding; eye-tracking; visual attention; perceived workload; sustainable micromobility

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1. Introduction

The expansion of sustainable urban micromobility has given cities new ways to ease congestion on the road network and to promote increased engagement in active transport

[1,2]. E-scooters have become a common mode of urban micromobility, used for both private trips and shared rental services [3]. Their popularity is linked to their efficient electric motors, their ability to move easily through different types of urban infrastructure [4,5], and their flexibility for parking without relying on designated parking areas. This growth in usage has also been accompanied by a clear rise in reported crashes, serious injuries, and fatalities involving e-scooters across European Union (EU) countries [6]. At the same time, the growing presence of e-scooters in cities has introduced additional challenges related to interactions with pedestrians and other road users and the suitability of existing infrastructure for e-scooter operation [4]. These safety concerns highlight the need for a clearer understanding of how rider behaviour interacts with infrastructure conditions. Research has demonstrated that understanding rider behaviour, together with the infrastructure context in which it occurs, is essential for improving safety outcomes [7,8], guiding infrastructure design [4], refining operational practices [9], and enhancing rule enforcement [10]. Rider behaviour is often analysed through interviews, surveys, and observational research [11–13]. However, these methods can encounter challenges, such as responses influenced by personal interpretation [14].

Eye-tracking methods have been increasingly used in micromobility research to record gaze behaviour and examine how riders distribute their visual attention during riding tasks [2,15]. Since fixation and saccade measures are widely used to describe visual processing, they provide suitable indicators for examining riders' visual attention across different infrastructure conditions [16–18]. Gaze behaviour provides a useful indicator of cognitive processing demand, as changes in gaze metrics and their variability have been associated with cognitive workload [19–21]. Assessing perceived workload alongside visual attention provides complementary insight into how riders respond to different infrastructure conditions and operational demands [22,23].

Field-based eye-tracking studies have used gaze behaviour to examine how micromobility users monitor the traffic environment and respond to potential conflict situations in shared-road settings [15,16]. Systematic reviews of cycling studies indicate that gaze behaviour varies with infrastructure complexity and traffic conditions, reflecting changes in visual attention across different riding environments [16,17,24]. Although cycling and e-scooter riding are not identical, both modes operate within similar urban infrastructure conditions and require riders to monitor surrounding road users and potential conflicts [2]. Therefore, findings from cycling research provide a useful basis for examining how infrastructure conditions may influence visual attention among e-scooter riders. In a field eye-tracking study on a shared road, Pashkevich et al. compared pedestrians, cyclists, and e-scooter riders and found that cyclists and e-scooter users devoted a greater proportion of visual attention to the road ahead and to other road users than pedestrians, indicating active monitoring of potential conflicts during riding [15]. However, the study was limited to a single shared-road environment and did not examine variation in gaze behaviour across different infrastructure types or riding scenarios. Research by Kegalle et al. [2] focused on e-scooter users, examining how riders allocate visual attention across various types of transport infrastructure. Although the study offers valuable insights into gaze behaviour under real-world conditions, the authors note several limitations, including a small sample size, data loss due to speed and device malfunctions, and reliance on a predefined route primarily within park environments [2]. These factors may not fully capture the complexity of e-scooter interactions in dense or highly congested urban settings. E-scooter use has been documented across diverse urban built environments and spatiotemporal contexts [25,26]. Consequently, planners face uncertainty about which infrastructure conditions best support safe e-scooter operation and how riders adapt their visual and behavioural strategies in these contexts.

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Variations in infrastructure type can influence rider behaviour, affect the suitability of facilities for e-scooter use, and shape interactions with pedestrians, cyclists, and motor vehicles. However, research examining e-scooter rider behaviour across multiple infrastructure types remains limited. Key questions remain regarding how selected route conditions are associated with visual attention and perceived workload. The present study examines how three selected urban route conditions are associated with e-scooter riders' visual attention and perceived workload under naturalistic conditions. By comparing routes with different infrastructure characteristics and overall complexity levels, this study evaluates route-level differences in visual attention and perceived workload. Because one route represented each route condition, this study focuses on route-level differences rather than general effects of infrastructure types. The findings provide evidence for identifying route-related visual and workload demands that should be considered when designing safer micromobility environments and developing appropriate regulations for e-scooter use.

2. Materials and Methods

2.1. Study Design Overview

The methodology consisted of several stages: route selection, route characterization and complexity assessment, field-based experimentation, data collection, and statistical analysis. The overall study workflow is presented in Figure 1.

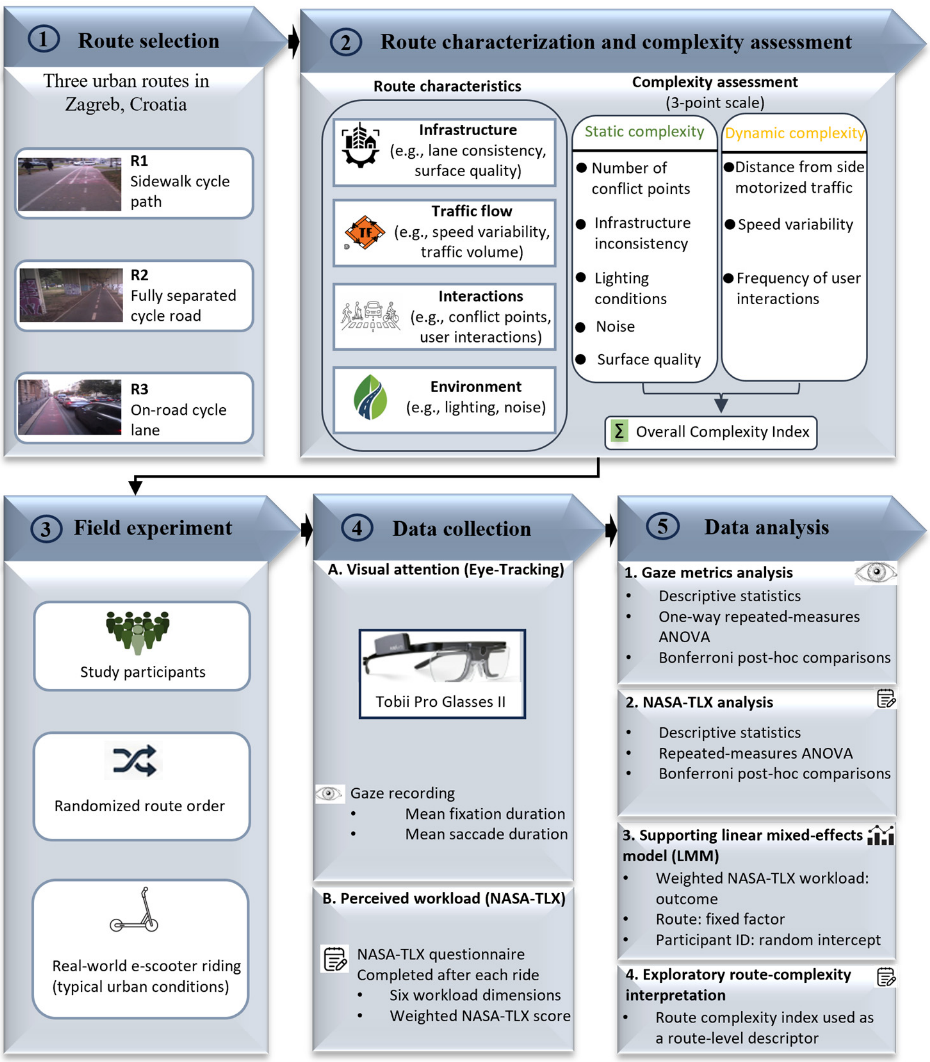

Figure 1. Methodological workflow of the study.

2.2. Participants, Apparatus, and Test Procedure

A sample of 28 adults (age: 30.0 ± 5.1 years) took part in the study, including 21 males and 7 females. Although efforts were made to recruit a more gender-balanced sample, fewer female participants were available. Previous studies have also reported higher e-scooter use among males than females [27,28]. All participants were volunteers and were not compensated for their participation. Participants were eligible if they were adults, were able to operate an e-scooter safely under the field-test conditions without wearing prescription glasses, and provided informed consent. No additional formal screening variables concerning visual acuity, corrective-lens use, neurological conditions, medication use, alcohol consumption, or sleep status were recorded for the present analysis. Therefore, these factors were not included as eligibility criteria or statistical covariates. Each participant was provided with an e-scooter and safety equipment (helmet, knee and elbow protection, and a reflective vest). The experimental setup was designed to capture rider responses under real-world infrastructure conditions. Four e-scooter models were used in the experiment: E-Goni S22, E-Goni S19 PRO, Xiaomi Mi Electric Scooter 5 MAX GL, and Xiaomi Mi Electric Scooter 5. These models represent commonly sold e-scooter types in Croatia. All four models had 10-inch wheels and a maximum speed limited to 25 km/h, while they differed in motor power, vehicle mass, tire type, suspension, and braking configuration. Their main technical characteristics are summarized in Appendix B. The sample consisted mainly of riders with no or limited previous e-scooter experience. More precisely, 71% of participants reported riding an e-scooter rarely (1 or fewer days per week), 25% occasionally (2–4 days per week), and one participant reported riding every day.

Gaze behaviour was recorded using Tobii Pro Glasses 2 at a sampling frequency of 50 Hz. The system incorporates a full high-definition (Full HD) scene camera with a field of view of approximately 82° horizontally and 52° vertically. Under optimal measurement conditions, the manufacturer-reported average binocular gaze accuracy is approximately 0.62° (standard deviation [SD] = 0.23°), with a precision of approximately 0.05° (SD = 0.10°). Before each experimental ride, the glasses were fitted individually to the participant after the helmet had been positioned. Calibration was performed using the Tobii calibration target according to the manufacturer's procedure, with the target positioned approximately 80–120 cm from the participant. Participants were instructed to fixate on the calibration marker during calibration. Calibration quality was checked before recording, and calibration was repeated when gaze positioning was not satisfactory. Calibration was therefore performed separately before each experimental ride.

The recordings were subsequently imported and processed in Tobii Pro Lab, version 26.10.2526. Gaze data were processed in Tobii Pro Lab using the Tobii Identification by Velocity Threshold (I-VT) Attention filter. Consecutive gaze samples were classified according to their angular velocity using a velocity threshold of 100°/s, with a minimum fixation duration of 60 ms. The processing settings included moving-median noise reduction, averaging of gaze data from both eyes, disabled gap interpolation, and merging of adjacent fixation events separated by no more than 75 ms and 0.5°.

Periods without valid gaze samples, including blinks and temporary loss of eye detection, were not included in fixation-duration calculations. Head movements were inherent to the naturalistic riding task and were accommodated by the head-mounted eye-tracking system. No additional manual correction for head movement or motion artefacts was applied.

Participants were instructed to follow the predefined routes, comply with traffic rules, and ride as they normally would. Ethical and data-security guidelines established by the University of Zagreb were followed throughout the study, and written informed consent was obtained from all participants. After completing each ride, participants were

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also asked to complete a post-test National Aeronautics and Space Administration Task Load Index (NASA-TLX) questionnaire [29] to report their perceived workload. Perceived workload was evaluated using the six NASA-TLX dimensions (a sliding scale without numbers), including mental demand, physical demand, temporal demand, effort, frustration, and performance. NASA-TLX ratings were collected following each ride. In this study, the weighted NASA-TLX score was used as the main overall workload outcome. In the questionnaire used in this study, lower Performance ratings represented better perceived performance, whereas higher ratings represented poorer perceived performance and therefore greater workload. Accordingly, all six dimensions were coded in the same direction, with higher values indicating greater workload, and no reverse coding of the Performance dimension was required. For each participant and route, each dimension score was multiplied by its pairwise-comparison weight, the weighted values were summed across the six dimensions, and the total was divided by 15, corresponding to the 15 pairwise comparisons. The six individual dimensions were retained descriptively to support interpretation.

Each route was completed on a separate day to minimize fatigue and learning effects. The order of the routes (R1–R3) was randomized across participants to control for potential order effects. Each participant completed all three routes on separate days. The experimental rides were conducted on weekdays during working hours and outside the morning and afternoon peak periods. Testing was carried out under generally stable daytime weather and visibility conditions. However, because the experiment was conducted under naturalistic field conditions, pedestrian activity, traffic conditions, and other environmental factors could not be fully standardized across all rides. To further reduce fatigue and learning effects, a minimum interval of one day was scheduled between rides. NASA-TLX was completed immediately after each route, after removing the protective equipment and eye-tracking glasses. Two investigators were present during the field study to keep the procedure consistent across participants. Before the experimental rides, participants completed a short warm-up ride and were asked whether they felt safe and confident operating the e-scooter. Participants were informed that they could stop the experiment at any time if they felt unsafe or overwhelmed.

2.3. Experimental Routes

The experiments were conducted in Zagreb, Croatia. For the analysis of gaze behaviour, three routes were selected to represent different urban route and traffic-environment conditions. The main characteristics of the selected routes are summarized in Table 1. Because each route differed in several characteristics at the same time, the routes were treated as combined route environments rather than isolated infrastructure-type treatments.

The selection of the experimental routes adhered to the following principles: (1) inclusion of different types of urban intersections to facilitate the analysis of participants' visual search behaviour when traversing intersections; (2) diverse urban settings, covering business and residential areas, university-related facilities, parking areas, and an underpass; (3) varying levels of interaction with pedestrians, cyclists, e-scooter riders, and motorized traffic; and (4) different levels of separation from motorized traffic and road conditions that allowed safe and controlled testing. These criteria were used to ensure that each route represented a distinct infrastructure condition with different levels of interaction and operational demand. The experimental routes were selected prior to data collection to represent distinct combinations of infrastructure and traffic-environment characteristics while ensuring the feasibility and safety of repeated field testing. The selection was guided by the objectives of the study and by the need to include routes with clearly different operational conditions.

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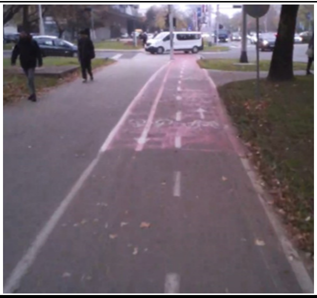
According to Table 1, the first route (R1) consisted of a cycle path on the sidewalk alongside pedestrian activity and was physically separated from motorized traffic. It passed through a mixed business and residential area with university and parking facilities and included multiple intersections. The second route (R2) consisted of a fully separated cycle road beneath an overpass, with no intersections and limited interaction with other road users. The third route (R3) consisted of an on-road cycle lane alongside motorized traffic. It passed through a mixed business and residential area characterized by one-way traffic flow and included several signalized intersections and close proximity to surrounding vehicles. The selected routes therefore differed in both infrastructure-related and traffic-environment characteristics, including intersection density, signalized intersections, pedestrian activity, surface quality, lighting, noise, and proximity to motorized traffic. Previous micromobility research has examined how cycling-facility context and individual characteristics are associated with travel behaviour and route choice [30].

Table 1. Infrastructure and traffic characteristics of the selected experimental routes.

Category	Variable	R1	R2	R3
General	Route length (km)	0.8	0.7	0.9
	Infrastructure type	Cycle path on the sidewalk, alongside pedestrian activity	Fully separated cycle road	On-road cycle lane alongside motorized traffic
	Lane width (m)	1.0	1.0	1.5
	Urban context	Mixed business and residential area, University facilities and parking areas	Beneath an overpass	Mixed business and residential area
	Infrastructure consistency	Low	High	Moderate
Traffic & flow	Motorized traffic direction	Two-way	Not present	One-way
	Cyclist and e-scooter traffic flow direction	Two-way	Two-way	One-way
	Proximity to adjacent motorized traffic	Low	None	High
	Speed variability	High	Low	Moderate
Intersections	Total number of intersections	6	0	6
	Number of signalized intersections	2	0	6
	Number of conflict points during signalized green phases	10	0	4
User interaction	Pedestrian density along the route	High	Low	Low
	Cyclist and e-scooter rider density	Moderate	Moderate	Moderate

	Interaction frequency	High	Low	Low
Environment	Visibility conditions	Good (open view)	Good (open view)	Good (open view)
	Lighting conditions	Good	Moderate (reduced beneath the overpass)	Good
	Noise	Moderate	Low	High
	Surface quality	Poor	Good	Good
Representative images of the selected experimental routes	-			

Note: Qualitative route characteristics were classified based on field observations conducted during the experimental route assessment.

2.4. Environmental Complexity Assessment

To obtain a structured semi-quantitative description of the riding routes, variables that could be quantified were extracted. Based on these values, the complexity of each route was calculated. While Table 1 presents a descriptive illustration of the three tested routes in the urban environment, Table 2 presents structured ordinal assessments of individual route features. The index was used to describe the selected routes and not as a validated general predictor of gaze behaviour, workload, or safety outcomes.

The route characteristics were scored on a 0–3 ordinal scale, with 1 representing the most favourable conditions (least demanding) and 3 representing the least favourable conditions (most demanding). If a condition was absent, a score of 0 was assigned (for example, the number of intersections on R2). Higher scores represented conditions expected to increase operational and visual complexity for e-scooter riders. The detailed scoring criteria for each component are provided in Appendix A.

The assessment was independently conducted by three co-authors with expertise in traffic safety and infrastructure. When differences in scoring occurred, the final score was agreed upon through repeated observations and discussion.

The variables were divided into two categories: static (environmental) complexity and dynamic (traffic) complexity. The first category refers to unchangeable parameters related to the environment and infrastructure. The second category contains variables related to the dynamic component, that is, the traffic flow itself. The scores were derived from field observations and examination of video recordings obtained during the experimental rides.

Overall complexity is the sum of all scores, with the highest score indicating the route rated as the most complex. Given that all rides occurred during the day, the description of conditions refers to daytime. This approach was used to characterize differences in route complexity and to support descriptive interpretation of the gaze and workload results. Because only three unique route-level complexity values were available, the index was interpreted descriptively and exploratorily. Separate static and dynamic scores were discussed as route descriptors but not treated as reliable independent predictors. Static, dynamic, and overall complexity scores were retained to characterize the three routes. All components contributed equally to the summed score because the index was intended as a simple exploratory descriptor, not a validated weighted scale of relative importance.

With only three routes, alternative weighting schemes or separate inferential models for static and dynamic complexity would not provide reliable independent estimates.

Table 2. Calculated static, dynamic, and overall complexity indices for the selected experimental routes.

Category	**Variable**	**R1**	**R2**	**R3**
Static (environmental) complexity	Infrastructure inconsistency	3	1	2
	Number of conflict points	3	0	2
	Lighting conditions	1	2	1
	Noise	2	1	3
	Surface quality	3	1	1
	Total	12	5	9
Dynamic (traffic) complexity	Distance from side motorized traffic	1	0	3
	Speed variability	3	1	2
	Frequency of user interactions	3	1	1
	Total	7	2	6
Complexity overall		19	7	15

2.5. Data Analysis

2.5.1. Route-Based Statistical Comparisons

A descriptive analysis of eye movement behaviour was conducted using gaze metrics including mean fixation duration and mean saccade duration to characterize visual attention during e-scooter riding across the selected routes. Subsequent statistical analyses examined differences in gaze-related measures across routes. The analysis focused on global temporal gaze metrics that could be calculated consistently across complete naturalistic routes. Additional area-of-interest (AOI)-based and spatial gaze metrics were not included in the present analysis.

The effect of route condition on visual attention was examined using one-way repeated-measures analyses of variance (ANOVAs), with route as a within-subject factor. The assumption of sphericity was assessed using Mauchly's test. When violations of sphericity were identified, Greenhouse–Geisser corrections were applied. Bonferroni-adjusted p-values were used for pairwise route comparisons. As sensitivity checks, non-parametric Friedman tests and Bonferroni-adjusted Wilcoxon signed-rank tests were conducted for the main repeated-measures outcomes. Residual diagnostics were inspected using quantile–quantile (Q–Q) plots and Shapiro–Wilk tests.

Perceived workload was measured using the National Aeronautics and Space Administration Task Load Index (NASA-TLX) questionnaire. Differences in the weighted NASA-TLX workload score across routes were analysed using one-way repeated-measures analyses of variance (ANOVAs), with route as a within-subject factor. Sphericity was evaluated using Mauchly's test, and Greenhouse–Geisser corrections were applied when necessary. Significant main effects were followed by Bonferroni-adjusted post hoc paired comparisons between routes. Effect sizes for paired route comparisons were calculated as paired-samples Cohen's d_z, defined as the mean within-participant difference divided by the standard deviation of the paired differences. The sign indicates the direction of the listed route contrast; for example, R1–R2 represents R1 minus R2. Ninety-five percent confidence intervals were calculated for each effect size. Pearson correlation analysis was used to explore associations between the six NASA-TLX dimensions and the weighted NASA-TLX workload score. To control for multiple testing, p-values were adjusted using Holm correction for the correlation analyses; Bonferroni correction was retained for post hoc route comparisons.

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2.5.2. Linear Mixed-Effects Modeling

Linear mixed-effects models (LMMs) were used to further examine the associations between route condition and weighted NASA-TLX workload while accounting for repeated observations within participants. Route was retained as the primary fixed factor because the study included only three selected routes and only one route represented each route condition. Since each participant completed all three routes, participant ID was included as a random intercept to account for repeated observations within individuals. The supporting route-based LMM was fitted using maximum likelihood estimation. The main supporting mixed-effects model used the weighted NASA-TLX score as the outcome and route as the fixed factor, with participant ID included as a random intercept. Complexity-based models were treated as exploratory only because repeating three route-level complexity scores across participants does not create independent route-level observations. Statistical significance was evaluated at $p < 0.05$.

3. Results

This section presents the results for visual attention and perceived workload during e-scooter riding. Gaze behaviour outcomes are reported across the selected routes, followed by perceived workload results and supporting mixed-effects analysis and exploratory route-complexity interpretation.

3.1. Gaze Metrics Across Selected Routes

3.1.1. Descriptive Analysis of Gaze Metrics

This section presents a descriptive summary of the main gaze indicators recorded in the present study. Table 3 shows the mean saccade and fixation durations, in milliseconds, across the three selected routes. The descriptive results showed that mean saccade duration remained relatively consistent across the three routes, ranging from 32.92 ms in R2 to 34.66 ms in R3. In contrast, greater variation was observed in mean fixation duration. The highest mean fixation duration was recorded in R2 (409.58 ms), followed by R3 (314.08 ms) and R1 (278.00 ms).

Table 3. Descriptive analysis of gaze metrics across the selected routes.

Route	Gaze Metrics	
	Mean Saccade Duration (ms)	Mean Fixation Duration (ms)
R1	34.34 ± 1.77	278.00 ± 54.96
R2	32.92 ± 3.03	409.58 ± 220.45
R3	34.66 ± 2.68	314.08 ± 92.74

3.1.2. Statistical Analysis of Gaze Metrics Across Selected Routes

The influence of route condition on gaze behaviour was assessed using a repeated-measures ANOVA across three distinct routes, considering mean fixation duration and mean saccade duration (Table 4). Mauchly's test indicated that the assumption of sphericity was violated for both mean fixation duration (W = 0.436, $p < 0.001$) and mean saccade duration (W = 0.482, $p < 0.001$). Therefore, Greenhouse–Geisser corrections were applied (εGG = 0.639 and 0.659, respectively). The analysis revealed a statistically significant effect of route on mean fixation duration after the Greenhouse–Geisser correction, indicating route-related differences in riders' visual attention. In contrast, no statistically significant effect was found for mean saccade duration.

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Table 4. Repeated-measures ANOVA results for route effects on gaze metrics.

Dependent Variable	F	*p* (GG-Corrected)	Partial η^2	df1 (GG)	df2 (GG)
Mean fixation duration (ms)	7.820	0.005	0.225	1.279	34.524
Mean saccade duration (ms)	3.550	0.057	0.116	1.318	35.577

Note. GG = Greenhouse–Geisser; df = degrees of freedom.

To identify route-specific differences in fixation behaviour, Bonferroni-adjusted post hoc comparisons were performed (Table 5). The results indicated that only the comparison between R1 and R2 remained statistically significant for mean fixation duration after the Bonferroni correction, with a moderate-to-large paired effect size, suggesting a substantial difference in fixation behaviour between the two selected routes. Comparisons involving R3 did not reach statistical significance after the Bonferroni correction for this metric. The Friedman sensitivity test for fixation duration did not reach statistical significance (p = 0.091), indicating that the fixation-duration result should be interpreted cautiously. For mean saccade duration, the repeated-measures ANOVA did not show a significant route effect after Greenhouse–Geisser correction, $F(1.318, 35.577) = 3.55$, $p_{GG} = 0.057$; the Friedman sensitivity test was also not significant (p = 0.066).

Table 5. Bonferroni-corrected post hoc comparisons of mean fixation duration across routes.

Comparison	Mean Difference (ms)	Bonferroni-Adjusted *p*	Cohen's d_z	95% CI for d_z
R1–R2	−131.58	0.0069	−0.637	−0.983 to −0.376
R1–R3	−36.08	0.142	−0.393	−0.706 to −0.066
R2–R3	95.50	0.0877	0.435	0.118 to 0.782

Note. Mean differences and effect-size signs are defined according to the listed route comparison (e.g., R1–R2 = R1 minus R2). Cohen's dz was calculated from paired within-participant differences. Statistical significance of pairwise comparisons is based on Bonferroni-adjusted *p*-values; effect-size confidence intervals are 95% bootstrap intervals. CI = confidence interval.

3.2. NASA-TLX Workload Analysis

3.2.1. Descriptive Analysis of NASA-TLX Workload Ratings

Perceived workload was assessed using the NASA-TLX questionnaire across the three selected routes. The weighted NASA-TLX score was used as the primary overall workload outcome. Descriptive statistics for the weighted score are presented in Table 6, and its distribution across routes is illustrated in Figure 2. Weighted workload was highest on R3, lowest on R2, and intermediate on R1.

Table 6. Descriptive statistics for the weighted NASA-TLX workload score.

Route	Mean	SD	Median	Min	Max
R1	5.80	4.08	4.87	1.00	14.00
R2	2.50	1.65	2.40	0.80	7.87
R3	8.58	4.13	7.93	1.00	14.87

The six individual NASA-TLX dimensions were retained as supporting descriptive measures and are presented in Table 7. These dimension-level scores were not used as the primary overall workload outcome; the weighted NASA-TLX score was used for the main workload analyses.

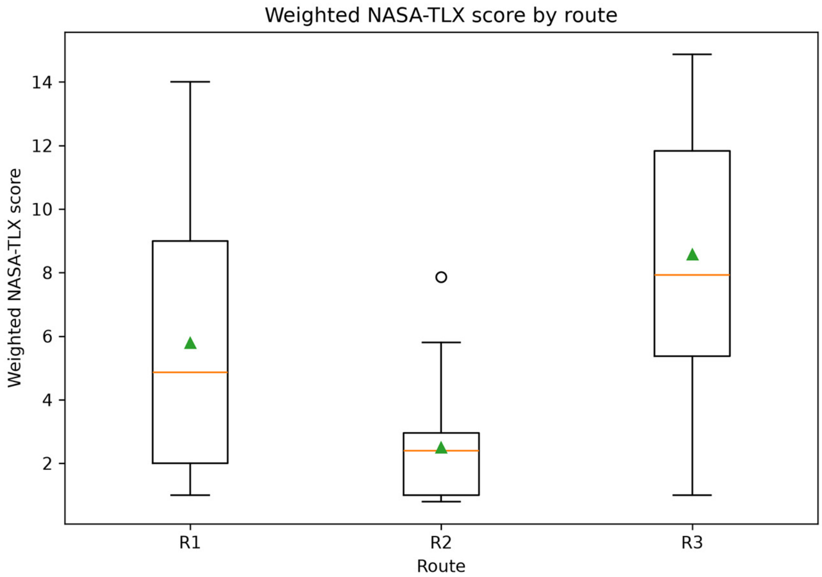

Figure 2. Distribution of weighted NASA-TLX workload scores across the three selected routes.

Table 7. Descriptive statistics for the six individual NASA-TLX dimensions across the selected routes.

Group	Category	Mental (Mean ± SD)	Physical (Mean ± SD)	Temporal (Mean ± SD)	Performance (Mean ± SD)	Effort (Mean ± SD)	Frustration (Mean ± SD)
Location	R1	6.50 ± 5.43	6.11 ± 4.76	5.96 ± 4.91	4.86 ± 5.96	7.18 ± 5.16	6.71 ± 5.19
	R2	3.54 ± 4.70	2.61 ± 3.69	2.57 ± 2.52	2.04 ± 3.45	3.21 ± 3.21	2.82 ± 3.33
	R3	9.50 ± 4.83	7.54 ± 4.65	6.79 ± 4.49	6.18 ± 5.70	10.36 ± 4.82	9.00 ± 5.16

3.2.2. Statistical Analysis of NASA-TLX Workload Ratings Across Selected Routes

The weighted NASA-TLX score differed significantly across the three selected routes, $F(2, 52) = 25.06$, $p < 0.001$, $\eta G^2 = 0.346$. Bonferroni-adjusted pairwise comparisons were significant for R1–R2 ($p = 0.0006$), R1–R3 ($p = 0.047$), and R2–R3 ($p < 0.001$). The Friedman sensitivity test also indicated a significant overall route effect, $\chi^2 = 23.79$, $p < 0.001$. In the non-parametric pairwise sensitivity analysis, the R1–R3 comparison was less robust, whereas R1–R2 and R2–R3 remained significant. The corresponding results are summarized in Table 8.

Table 8. Route comparisons for the weighted NASA-TLX workload score.

Analysis	Statistic	*p*-Value	Interpretation
Weighted NASA-TLX Repeated-measures ANOVA	$F(2, 52) = 25.06$, $\eta G^2 = 0.346$	<0.001	Significant route effect
Bonferroni R1–R2	—	0.0006	R1 higher than R2
Bonferroni R1–R3	—	0.047	R3 higher than R1; cautious
Bonferroni R2–R3	—	<0.001	R3 higher than R2
Friedman sensitivity test	$\chi^2 = 23.79$	<0.001	Significant route effect

Note. Parametric and non-parametric results were used together to support a cautious interpretation of route differences.

Pearson correlations were examined among the six NASA-TLX dimensions and the weighted NASA-TLX score. Holm correction was applied to control for multiple comparisons. The complete correlation matrix is presented in Table 9. The weighted NASA-TLX score showed its strongest associations with frustration ($r = 0.873$), effort ($r = 0.865$), and mental demand ($r = 0.808$).

Table 9. Pearson correlation matrix for the six NASA-TLX dimensions and the weighted NASA-TLX workload score.

Variable	Mental	Physical	Temporal	Performance	Effort	Frustration	Weighted NASA-TLX
Mental	1.000	0.771	0.637	0.273	0.735	0.708	0.808
Physical	0.771	1.000	0.753	0.236	0.649	0.636	0.701
Temporal	0.637	0.753	1.000	0.266	0.597	0.612	0.680
Performance	0.273	0.236	0.266	1.000	0.346	0.309	0.539
Effort	0.735	0.649	0.597	0.346	1.000	0.843	0.865
Frustration	0.708	0.636	0.612	0.309	0.843	1.000	0.873
Weighted NASA-TLX	0.808	0.701	0.680	0.539	0.865	0.873	1.000

Note. All correlations remained significant after Holm correction. Overall Cronbach's α across NASA-TLX dimensions was 0.850 as a supplementary check, but the weighted score was used as the main overall workload outcome.

3.3. Supporting Mixed-Effects Analysis and Exploratory Route-Complexity Interpretation

A supporting linear mixed-effects model was fitted with weighted NASA-TLX workload as the outcome, route as the fixed factor, and participant ID as a random intercept. Compared with R1, R2 was associated with lower weighted workload, whereas R3 was associated with significantly higher weighted workload. The fixed-effect estimates are presented in Table 10. Complexity-based mixed models were not retained as primary predictive models because the complexity index had only three unique route-level values and several complexity-based models were unstable or diagnostically weak. The complexity index was therefore retained as an exploratory route-level descriptor. The LMM was used as a supporting analysis; the Bonferroni-adjusted repeated-measures comparisons in Table 8 remained the primary basis for pairwise route interpretation.

Table 10. Route-based linear mixed-effects model for weighted NASA-TLX workload.

Predictor	β	95% CI	*p*-Value	Interpretation
R2 vs. R1	−3.29	−4.92 to −1.67	<0.001	Lower workload on R2
R3 vs. R1	2.76	1.11 to 4.40	0.001	Higher workload on R3

Note. Participant ID was included as a random intercept; R1 was the reference route.

The corresponding model-fit and variance-component statistics are summarized in Table 11.

Table 11. Fit statistics for the route-based weighted NASA-TLX linear mixed-effects model.

Metric	Value
AIC	447.15
BIC	459.24
Random-intercept variance	2.022
Residual variance	9.640
ICC	0.173
Marginal R^2	0.372
Conditional R^2	0.481

Note. AIC = Akaike information criterion; BIC = Bayesian information criterion; ICC = intraclass correlation coefficient.

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Residual diagnostics for the route-based weighted NASA-TLX LMM did not indicate a significant departure from normality (Shapiro–Wilk W = 0.981, p = 0.257).

4. Discussion

This study investigated route-level differences in visual attention and perceived workload among e-scooter riders under real-world riding conditions. By integrating objective eye-tracking measures with subjective workload ratings, the study provides a broader understanding of how riders' visual attention and perceived workload vary across the selected urban route conditions. The results should therefore be interpreted as differences among three selected routes, not as general effects of infrastructure types.

Three routes were selected for the study. Table 1 presents the detailed characteristics of each route, while Table 2 summarizes the calculated complexity scores. Based on these scores, R1 represented the most complex route within the exploratory complexity assessment. This route included a cycle path alongside pedestrian activity, frequent user interactions, multiple intersections and conflict points, low infrastructure consistency, high speed variability, and low surface quality. In contrast, R2 represented the least complex route. It consisted of a fully separated cycle road with no intersections or conflict points, no adjacent motorized traffic, low interaction frequency, good infrastructure consistency, and good surface quality. R3 had an intermediate level of complexity. It included an on-road cycle lane alongside motorized traffic, close proximity to surrounding vehicles, several signalized intersections, moderate speed variability, and high noise levels. Because these characteristics varied together, the observed differences cannot be attributed to one isolated factor such as physical separation, surface quality, traffic proximity, or intersection density.

After examining the characteristics and complexity of the selected routes, gaze metrics were assessed across the three selected routes, as reported in Table 3. Statistical analyses were then conducted to examine the effect of route condition on riders' visual attention (Tables 4 and 5). The results showed that route condition had a statistically significant effect on mean fixation duration, whereas no statistically significant effect was identified for mean saccade duration. The route-specific comparisons presented in Table 5 showed that only the difference between R1 and R2 remained statistically significant for mean fixation duration. Because the non-parametric sensitivity test did not reach significance, this finding should be interpreted cautiously, with the clearest pairwise difference observed between R1 and R2.

In line with these route-based statistical findings, the observed differences in mean fixation duration are consistent with the route characteristics and complexity scores reported in Tables 1 and 2. R1 was the most complex route, while R2 was the least complex. On R2, riders exhibited longer fixation durations, which may reflect more stable visual attention in a separated and predictable riding environment. This interpretation is consistent with the findings of Kegalle et al. [2], which suggest that separated and predictable infrastructure can support more stable gaze behaviour. Previous research has shown that intersections, crosswalks, and high pedestrian activity can increase visual workload and shift attention away from the riding path, whereas greater physical separation can support more focused and stable visual attention [16,18]. Cycling eye-tracking reviews also show that gaze metrics are sensitive to built-environment characteristics, road conditions, navigation demands, workload, and stress-related responses [16,17]. Previous research has shown that visual scanning changes under spatial uncertainty and varying road-infrastructure conditions [31,32]. Field research has also examined e-scooter gaze behaviour under urban riding conditions [33]. In contrast, the complex characteristics of R1 may have required riders to monitor several dynamic elements simultaneously.

The shorter fixation durations observed on this route may indicate increased visual scanning in response to greater uncertainty and interaction demands. However, shorter fixation duration may also reflect unstable gaze, motion artefacts, reduced processing time, or distraction in field-based riding conditions. Longer fixation duration may indicate stable attention in some contexts but may also reflect processing difficulty or narrower monitoring of the environment. This interpretation is consistent with previous naturalistic studies showing that protected cycle facilities support more stable and focused gaze behaviour, whereas shared roads and intersections can result in more scattered gaze patterns [32,33]. Similarly, experimental evidence indicates that low-quality surfaces increase near-field road monitoring and shift visual attention toward closer road sections [34]. The present study adds to this evidence by showing that mean fixation duration varied across selected routes with different combined infrastructure and traffic-environment characteristics. Fixation duration should not be interpreted as a direct safety measure because crashes, near-crashes, braking behaviour, steering stability, lateral position, or hazard detection were not measured.

The next stage of the analysis examined riders' perceived workload. The weighted NASA-TLX descriptive results (Table 6 and Figure 2) showed the highest workload on R3, the lowest workload on R2, and intermediate workload on R1. The individual NASA-TLX dimensions, presented descriptively in Table 7, showed a broadly similar pattern. Inferential analysis of the weighted NASA-TLX score (Table 8) confirmed a significant overall route effect, with Bonferroni-adjusted differences between R1–R2, R1–R3, and R2–R3. The Friedman sensitivity analysis also supported an overall route effect, although the R1–R3 contrast was less robust in the non-parametric pairwise analysis. However, the relationship between complexity and workload was not fully linear because R1 had the highest overall complexity score, while R3 showed the highest weighted NASA-TLX workload. Although the weighted R1–R3 comparison reached statistical significance (p = 0.047), this contrast was less robust in the non-parametric sensitivity analysis. This pattern is plausible because R1 and R3 had relatively similar complexity scores, and both represented more demanding route environments than R2.

These results suggest that the overall complexity index did not fully capture perceived operational difficulty, particularly the workload associated with proximity to motorized traffic and repeated signalized intersections on R3. Repeated signalized-intersection and stop-related demands may still have contributed to workload as part of the route experience. The static and dynamic components of the exploratory complexity index also help describe the route pattern without implying independent causal effects. R2 had the lowest static (5) and dynamic (2) scores. R1 had the highest static score (12) and the highest overall score (19), whereas R3 had an intermediate static score (9) but a relatively high dynamic score (6), reflecting close motorized-traffic exposure and repeated signal-related operational demands. This pattern helps explain why the highest perceived workload occurred on R3 even though R1 had the highest overall complexity score. These component scores are therefore used descriptively, not as statistically validated independent predictors.

A supporting LMM was used to examine route-level differences in weighted workload while accounting for repeated observations within participants. This model supported the route-based workload results: R2 was associated with significantly lower weighted workload than R1, whereas R3 was associated with significantly higher weighted workload than R1. Complexity-based mixed models were not retained as primary predictive models because only three unique route-level complexity scores were available and several models were unstable or diagnostically weak. Therefore, the complexity index is interpreted as an exploratory route-level descriptor, not as a validated continuous predictor. This interpretation is consistent with previous research showing that infrastructure and traffic characteristics can increase the perceived complexity of road situations [35]. This also clarifies the relationship between the pairwise gaze results and the earlier complexity-based interpretation: only the R1–R2 fixation comparison remained significant after Bonferroni correction, and the route-complexity scores should not be interpreted as evidence of a general linear relationship between fixation duration and complexity.

Taken together, the route-based gaze-metric and weighted NASA-TLX results showed that riders' visual attention and perceived workload varied across the selected routes. The linear mixed-effects model findings further indicated that weighted workload differed by route after accounting for repeated observations within participants. R2, which was characterized by separated and relatively consistent riding conditions, showed longer mean fixation durations and lower perceived workload than the other selected routes. These route-level patterns should not be generalized to separated infrastructure. Visual attention and perceived workload should therefore be interpreted as complementary outcomes rather than as evidence that fixation duration directly explains workload.

However, physical separation alone may not fully address the safety and interaction demands faced by e-scooter riders. Previous studies have shown that riders may still interact with pedestrians and cyclists on shared or cycling facilities, encounter conflict points at intersections, and experience safety concerns related to pavement conditions and proximity to motorized traffic [4,36]. Therefore, e-scooter infrastructure planning should not focus only on separation from motorized traffic but should also consider the broader route conditions that influence rider attention and workload. This is particularly important because previous research and policy discussions have emphasized that suitable e-scooter networks should account for safety, transport, and land-use characteristics [37]. In this context, combining infrastructure characteristics with behavioural indicators can provide a more human-centred basis for evaluating safety conditions and planning safer micromobility environments [38]. These findings are also relevant to sustainable micromobility planning. E-scooters can contribute to urban mobility, but their use depends on infrastructure conditions that do not create excessive visual and workload demands for riders. The results of this study show that selected route conditions were associated with riders' visual-attention patterns and perceived workload. Therefore, considering route complexity, infrastructure consistency, interaction demands, and surface conditions in planning decisions may help create riding environments that are more suitable for everyday e-scooter use and better aligned with sustainable urban mobility objectives. Overall, the present findings suggest that route-level human-factor evidence can support micromobility infrastructure evaluation, but it should be combined with direct safety indicators before drawing conclusions about route safety.

Limitations and Future Work

This study has several limitations that should be considered. First, the sample size was relatively small, and the participant group was not fully balanced in terms of gender. Therefore, the findings should be interpreted with caution and should not be generalized to all e-scooter riders. Second, participants had different levels of e-scooter riding experience, which may have influenced their perceived workload and gaze behaviour. More experienced riders may respond differently to the same infrastructure conditions than riders with limited experience. Participant-level factors such as visual status, medication use, sleep status, and other health-related conditions were not systematically recorded and may have contributed to individual variability in gaze behaviour and perceived workload. Although route order was randomised, possible order, learning, familiarity, and carryover effects could not be formally evaluated and therefore cannot be completely excluded.

Third, this study included only three selected urban routes in Zagreb. Although these routes represented different infrastructure conditions, they cannot capture the full range of possible e-scooter riding environments. Because this study included only three selected routes, the findings may also reflect route-specific characteristics, and broader validation across additional independent routes is needed. Fourth, only one route represented each route condition; therefore, route-specific variation cannot be separated from broader infrastructure-type effects.

Fifth, the routes differed in several characteristics at the same time, including intersections, surface quality, lighting, noise, pedestrian activity, traffic proximity, speed variability, and interaction frequency, so the independent effect of each factor could not be isolated. Although testing was conducted during comparable daytime periods and under generally stable weather and visibility conditions, traffic activity, pedestrian presence, and other field conditions could not be fully standardized across individual rides.

Sixth, field-based eye-tracking data may be affected by vibration, rapid head movement, changes in lighting, helmet or glasses position, and temporary loss of gaze detection. Participant- and route-specific valid-gaze percentages were not available in the processed dataset, so systematic differences in recording quality across routes could not be tested directly. Consequently, part of the observed variability in fixation duration may reflect measurement conditions in addition to differences in visual-attention behaviour. The gaze findings are therefore interpreted cautiously, and future field studies should report route- and participant-level gaze-validity measures alongside gaze outcomes.

Seventh, the complexity index was based on structured ordinal scoring and consensus assessment; it should be interpreted as an exploratory route-level descriptor rather than a validated predictor. Because only three routes were examined and no direct safety outcomes were measured, the present data cannot support validated safe/unsafe route-complexity thresholds; such thresholds require independent validation across a substantially larger set of routes.

Eighth, speed was not reported as a main covariate because the available speed values require further verification. Finally, this study did not directly measure crashes, near-crashes, braking behaviour, steering stability, lateral position, rule violations, or hazard detection; therefore, the results should be interpreted as visual-attention and perceived-workload outcomes, not direct safety outcomes.

Future studies could extend this work by examining a broader range of infrastructure complexity levels and related route characteristics. Larger and more diverse participant samples would also allow a more detailed assessment of whether riders' responses vary across individual characteristics. These extensions could support the development of more targeted infrastructure design recommendations and safety policies for e-scooter use. Because four e-scooter models were used, vehicle characteristics differed between some participants; however, each participant used the same assigned e-scooter on all three routes. Vehicle-related differences were therefore constant within participants, but model-specific effects cannot be separated from other between-participant variability.

The gaze analysis focused on route-level mean fixation and saccade duration and therefore does not capture the full spatial structure of visual attention. Dynamic AOI analysis, gaze dispersion or entropy, fixation-rate measures, and repeated comparable route segments should be considered in future work where consistent coding across environments is possible. Route familiarity was not measured at the level of the specific experimental routes and may have influenced gaze behaviour or workload. The naturalistic field design also means that pedestrian activity, traffic activity, lighting, and other environmental conditions could not be fully standardized across testing days.

The effective number of independent complexity conditions was three; therefore, repeating the same route-level complexity values across participants does not create independent continuous complexity observations, and the complexity index should not be generalized as a predictive scale. Generalizability is also limited to the selected Zagreb routes and the mainly novice/occasional young-adult sample; older adults, adolescents, riders with disabilities, experienced commuters, and users in other micromobility systems may respond differently.

5. Conclusions

The use of e-scooters has increased rapidly in recent years, accompanied by growing concerns about rider injuries and crash risks. These risks are not only related to rider behaviour but also to the infrastructure conditions in which riding takes place. Therefore, understanding how different infrastructure conditions influence rider behaviour is important for supporting safer e-scooter use. In this context, visual attention and perceived workload provide useful indicators of how riders respond to different riding environments. The present study investigated route-level differences in visual attention and perceived workload among e-scooter riders under real traffic conditions. A field-based experimental design was employed to compare rider behaviour across three selected routes characterised by different infrastructure and traffic-environment features. Because this study included one route for each route condition, the findings should be interpreted as preliminary route-level evidence rather than as general infrastructure-type effects. By combining field-based eye-tracking with weighted NASA-TLX assessment in a repeated-measures naturalistic design, this study provides preliminary route-level human-factor evidence for e-scooter research.

The results showed a significant route effect on mean fixation duration after the Greenhouse–Geisser correction, $F(1.279, 34.524) = 7.820$, $p = 0.005$, partial $\eta^2 = 0.225$, whereas mean saccade duration did not differ significantly across routes ($p = 0.057$). Among the pairwise fixation comparisons, only R1–R2 remained significant after Bonferroni correction; however, the non-parametric sensitivity test for fixation duration was not significant ($p = 0.091$), and this result should therefore be interpreted cautiously. Weighted NASA-TLX workload also differed significantly across routes, $F(2, 52) = 25.06$, $p < 0.001$, $\eta G^2 = 0.346$, with the highest workload observed on R3, the lowest on R2, and an intermediate level on R1. The supporting linear mixed-effects model showed lower weighted workload on R2 and higher weighted workload on R3 compared with R1. These findings indicate that the combined characteristics of the selected routes were associated with both riders' visual attention and perceived workload, while the exploratory route-complexity index should not be interpreted as a validated predictor or a direct measure of safety. These findings have practical implications for urban planning and transport policy, suggesting that infrastructure characteristics such as interaction frequency, conflict points, proximity to motorized traffic, speed-adaptation demands, infrastructure consistency, lighting conditions, noise, and surface quality should be carefully considered when designing safer micromobility environments. However, the results do not establish which infrastructure type is safest, because direct safety outcomes were not measured.

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and D.B. (Dario Babic); Visualization, S.R.; Supervision, D.B. (Dario Babic) and T.C.O.; Project Administration, D.B. (Dario Babic) and T.C.O.; Funding Acquisition, D.B. (Dario Babic) and T.C.O. All authors have read and agreed to the published version of the manuscript.

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Institutional Review Board Statement: The study was conducted in accordance with the Declaration of Helsinki and approved by the Ethics Committee of the University of Zagreb Faculty of Transport and Traffic Sciences (protocol code 053-01/25-01/05; 6 June 2025).

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: Because the study involved human participants and field-based eye-tracking recordings, raw video and raw gaze recordings cannot be openly shared due to privacy and ethical restrictions. Anonymized summary data, including route scores, gaze metrics, NASA-TLX results, and analysis outputs, can be made available from the corresponding author upon reasonable request. Statistical analysis settings and scripts may also be shared where permitted by the project and institutional data-management rules.

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Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A. Qualitative Scoring Criteria for Static and Dynamic Route-Complexity Components

Table A1. Qualitative scoring criteria for static and dynamic route-complexity components.

Component	Basis of Assessment	0	1	2	3
Infrastructure inconsistency	Visible changes in riding environment, path continuity, crossings, parking areas, and signal control	No relevant elements	Continuous and uniform infrastructure	Limited changes in infrastructure or riding conditions	Multiple discontinuities or transitions
Conflict points	Locations where rider path could intersect, merge, or conflict with another road-user stream	Absent	Low number	Moderate number	High number
Lighting conditions	General daytime visual conditions, including permanently shaded sections	Not applicable	Good and uniform daytime lighting	Reduced lighting or prolonged shadow	Substantially darker or pronounced changes
Noise	Observed environmental noise, mainly associated with motorized traffic proximity	No relevant noise	Low noise	Moderate traffic-related noise	High or continuous traffic-related noise
Surface quality	Patches, potholes, cracking, and larger pavement damage visible in field/video review	Not applicable	Good surface condition	Localized defects	Frequent or substantial defects
Proximity to motorized traffic	Physical and functional separation from motorized traffic	No motorized traffic	Physically separated	Limited separation/close proximity	Directly adjacent/no meaningful separation
Speed variability potential	Elements/actions likely to cause speed changes,	No speed adjustment elements	Few elements	Several elements	Frequent elements/actions

	stopping, yielding, signals, avoiding users				
Interaction frequency	Observed/potential interactions with pedestrians, cyclists, e-scooter users and motorized vehicles	No interactions	Low interaction frequency	Moderate interaction frequency	High interaction frequency

Note: Scores were assigned based on field examination of the routes and systematic review of recordings. Traffic volume was not explicitly included as a separate component of the complexity index.

Appendix B. Technical Characteristics of the E-Scooters Used in the Experiment

Table A2. Technical characteristics of the e-scooters used in the experiment.

Model	Motor Power/Max. Speed	Wheel/Tire	Mass	Suspension	Braking System
E-Goni S22	800 W/25 km/h	10 in., off-road tires	27.6 kg	Front and rear dual suspension	Front disc; rear disc + magnetic brake
E-Goni S19 PRO	500 W/25 km/h	10 in., pneumatic tires	16.2 kg	Front and rear suspension	Front magnetic; rear disc
Xiaomi Mi Electric Scooter 5 MAX GL	402 W nominal (1000 W max.)/25 km/h	10 in., tubeless	22.3 kg	Dual front hydraulic + dual rear suspension	Front drum + rear E-ABS
Xiaomi Mi Electric Scooter 5	350 W nominal (700 W max.)/25 km/h	10 in., tubeless	20.1 kg	Front spring suspension	Front drum + rear E-ABS

Note. Each participant used the same assigned e-scooter for all three experimental rides. The study was not designed to estimate independent vehicle-model effects. E-ABS = electronic anti-lock braking system.

Appendix C. Additional Visual Results

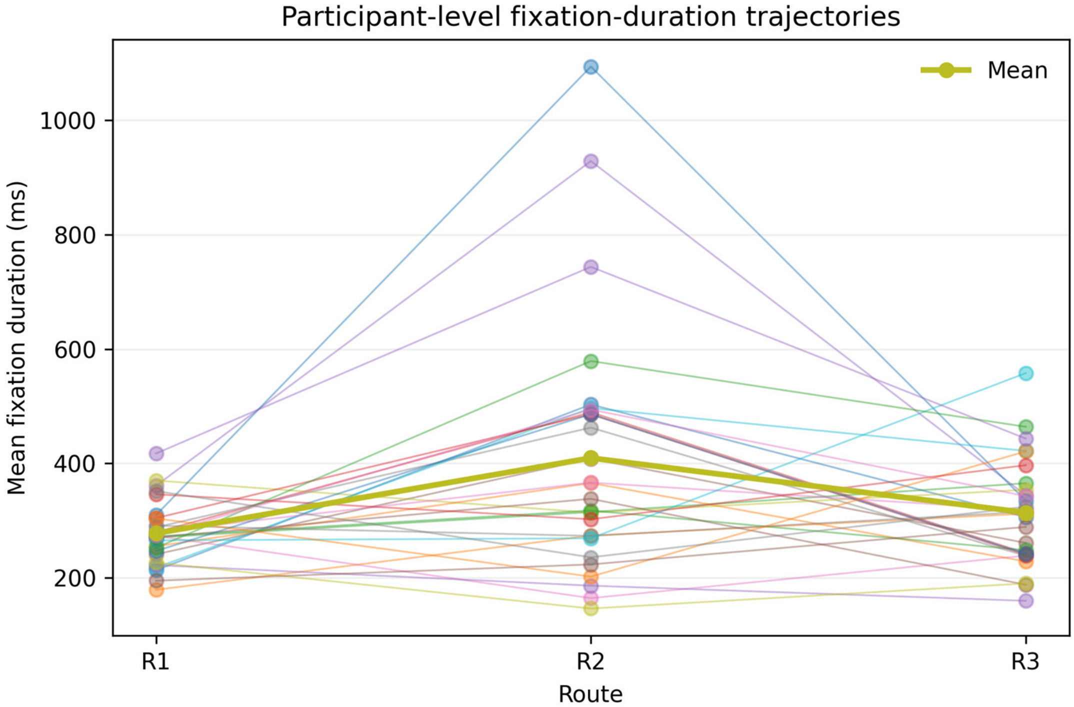

Figure A1. Participant-level mean fixation-duration trajectories across R1, R2, and R3.

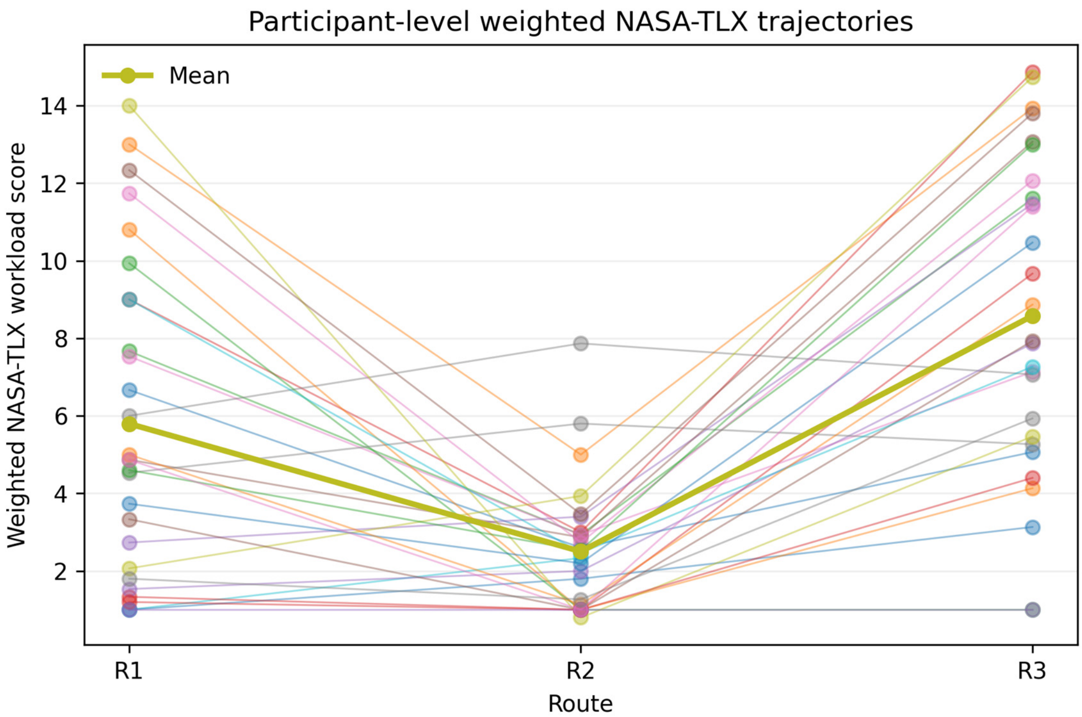

Figure A2. Participant-level weighted NASA-TLX trajectories across R1, R2, and R3. One R3 weighted score was missing; available paired trajectories are shown.

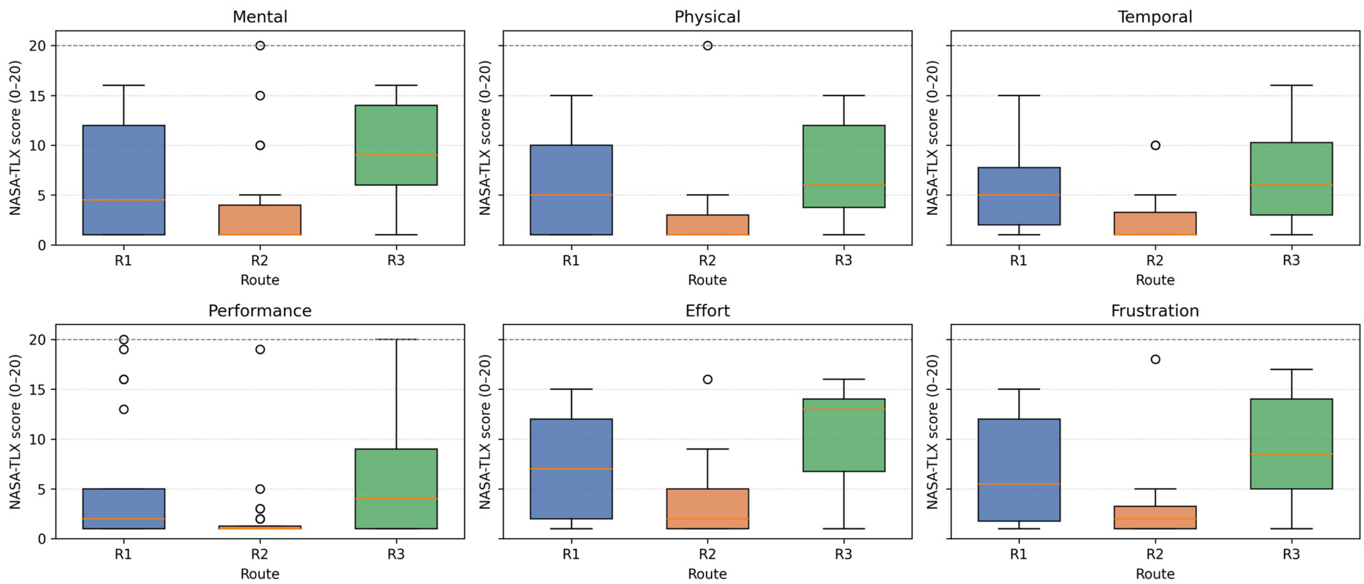

Figure A3. NASA-TLX workload boxplots for the six workload dimensions across three selected routes.

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