A Data-Driven Framework for Cycle Path Quality: Integrating User Perception and Sensing

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Abstract. This paper presents a comprehensive framework for assessing the quality of cycle path design by integrating subjective and objective measures of user experience. The approach combines static infrastructure attributes, dynamic data from multiple sensors, and user-reported perceptions into synthetic indicators that predict service quality. Unlike traditional infrastructure evaluation methods, this research explicitly considers how users perceive and react to real-world cycling conditions, bridging gaps in current methodologies that often isolate technical measurements from behavioral responses. A segmentation-based graph model of the cycling network, enriched with contextual and environmental features, enables fine-grained data fusion and analysis. On-road trials with different user and vehicle profiles collect multi-source data (accelerometers, GPS, eye-tracking, biometric sensors), aligned in time and space to produce synthetic indicators. Predictive models, developed through both econometric and machine learning approaches, evaluate the relationship between objective indicators and subjective quality ratings. Preliminary results show the feasibility of integrating diverse datasets into a scalable framework capable of informing design, planning, and policy.

Keywords: Cycle paths · quality of service · data fusion · synthetic indicators · predictive models · sustainable mobility

1 Introduction and State-of-the-Art

Recently, cycling has increasingly become the topic of multidisciplinary research, spanning from transport engineering, urban planning, and medical and human behaviour science. The global emphasis on sustainable urban mobility, climate-neutral cities, and promoting active lifestyles primarily drives this leap of interest.

Within this context, the literature has examined the interaction among three features: the physical characteristics of cycling infrastructure, the type of vehicle used (e.g., bicycle, e-bike, e-kick scooters), and the experience of cyclists, both objective (e.g., physiological or mechanical data) and subjective (e.g., comfort, safety perception). Studies

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have affirmed that the experience of cyclists is shaped by an interplay of factors, including road geometry, pavement quality, type of segregation from vehicular traffic, and environmental (context) conditions. For instance, [1] and [2] emphasised the relevance of vibrations in assessing the comfort of cycle paths, developing quantitative methods to evaluate infrastructure quality from a mechanical standpoint. Studies [3, 4] contributed to understanding how different micromobility devices respond to surface irregularities, using onboard sensors to monitor vibration levels and assess their implications for comfort and user health. However, while the relevance of vibrational feedback has been acknowledged, few studies integrate such data with other sensors or behavioural indicators. For instance, [5] combined subjective surveys with eye-tracking data to study how pavement condition affects perceived safety. Study [6] explored how infrastructure and land use characteristics influence gaze patterns during cycling. These approaches provide understanding of how cycle infrastructure affects attentional dynamics, but remain constrained to specific contexts, typically urban and intersections.

The use of eye-tracking, biometric sensors, and wearable devices is growing, especially in cognitive and health-oriented studies (e.g., [7–10]). These tools are often employed in isolation (i.e., just one device is applied) or under laboratory conditions. Moreover, "on-road" studies are limited and rarely synchronised across multiple sensor sources. This methodological gap reduces the generalisability and validity of findings. Moreover, the potential of integrating spatial network models with user-centred sensing remains largely unexplored, as opposed to the integration of passenger-oriented monitoring approaches with digital and web-based decision-support frameworks to support the assessment and management of transport service quality under real operational conditions [11].

An additional limitation of existing literature is the lack of comprehensive frameworks that relate data on infrastructure typologies, user variability, and trip characteristics [12] (e.g., purpose, frequency, and environment). Studies focus primarily on commuting, overlooking leisure or touristic cycling, which often occurs in peri-urban or rural settings and is influenced by different spatial, perceptual, and ergonomic factors. Other point out how cycling for non-systematic purposes is underrepresented in research, despite its growing relevance in sustainable mobility policies [13, 14]. Additionally, while some studies (e.g., [15, 16]) examine safety concerns, such as conflicts with turning vehicles or signalised intersections, they often isolate such events from broader systemic variables like vehicle type or road environment. Therefore, there is a gap in studies attempting to model related effects: for instance, how user stress responses change when different vehicle types (e.g., e-bike vs e-scooter) are used along varying infrastructure typologies, or how trip purpose influences attention, speed, and physiological state.

Consequently, to the best of the authors' knowledge, no studies in the reviewed literature provide a framework that simultaneously integrates:

- Granular network segmentation based on both geometric and dynamic criteria.
- Multi-source, time- and space-synchronised sensor data (e.g., GPS, accelerometer, biometric).
- User-level variability in terms of physical, cognitive, and experiential traits.

- Link between subjective and objective assessment of cycle path quality service [17]. A similar perspective has also been explored in public transport service quality assessment, where subjective user perceptions and objective performance indicators were jointly integrated within a unified evaluation framework [18].

The few studies related often rely on controlled simulations or virtual reality environments, which, although useful, cannot capture the variability of real-world cycling experiences. The spatial and contextual limitations of these environments make them critical for capturing the full complexity of infrastructure-user interactions. Therefore, this study aims to fill these gaps by proposing a rigorous and replicable framework grounded in real-world data. By constructing a segment-based graph of the road network and aligning it with sensor data collected during cycling trials, the study enables a multi-criteria analysis of service quality. The goal is to understand how the physical infrastructure and the surrounding environment interact with individual users and vehicles under realistic conditions, producing measurable effects on objective and subjective "comfort". Furthermore, by incorporating a range of user, vehicle, and cycle path types, the proposed framework enables for generalisable insights across diverse scenarios and derives guidelines. Lastly, it supports the development of predictive models that not only explain behaviour in retrospect but helps identify where and for whom the infrastructure underperforms. Therefore, it contributes to a more inclusive, data-informed approach to infrastructure evaluation and active mobility planning.

2 Methodology

The proposed methodology is structured into five sequential phases (Fig. 1), each of which addresses a key aspect of evaluating cycle infrastructure quality of service (QoS). The process integrates infrastructural attributes, user perceptions, and sensor-based measurements into a coherent framework that allows for both descriptive assessment and predictive modelling.

2.1 Phase 1. Preliminary Setup

The first phase establishes the analytical bases by building a graph-based representation of the cycling network and attributing relevant infrastructural and contextual variables. The network is modelled as a directed graph, where nodes correspond to intersections or points of divergence and links to homogeneous segments. Topological corrections, such as snapping and node consolidation, are applied to ensure connectivity, while segmentation rules divide the network according to geometric, functional, and land use discontinuities.

Moreover, each segment is enriched with systematic micro-scale data collection from open datasets, geoportals, and field surveys. These attributes include physical features, functional classifications, and contextual characteristics [e.g., 13]. The result is a fine-grained representation of infrastructure conditions, providing the reference layer for subsequent data integration.

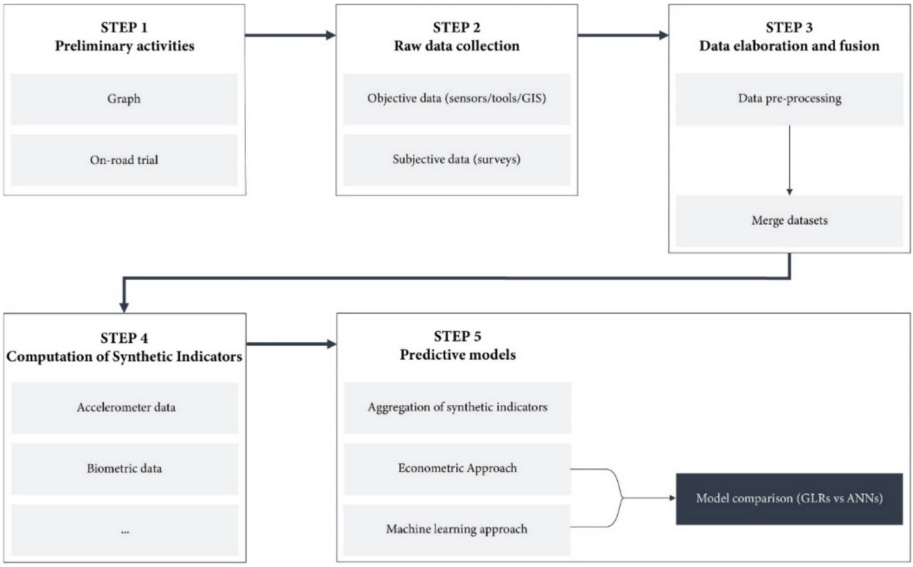

Fig. 1. Flowchart of the methodology.

2.2 Phase 2. Data Collection

In the second phase, both subjective and objective data are gathered through on-road trials.

Subjective data are obtained through structured questionnaires administered to trial participants. These surveys collect socio-demographic information and mobility habits, while also eliciting perceptions of comfort, safety, fatigue, and environmental quality during the ride. Responses are expressed on a Likert-type scale, providing user-centred evaluations for each segment.

Objective data derive from a set of sensors and devices: accelerometers to capture vibrations, GPS units to trace trajectories and speeds, eye trackers to monitor gaze behaviour, biometric wearables to record physiological responses (e.g., heart rate, electrodermal activity), and meteorological stations to contextualise environmental conditions. These multi-source streams document the physical, cognitive, and physiological dimensions of cycling.

The combination of these two data sources ensures that both experiential perceptions and measurable physical responses are captured for the same routes and conditions.

2.3 Phase 3. Data Elaboration and Fusion

Given the heterogeneity of devices, a dedicated pipeline is required to pre-process and integrate data. Outlier removal is performed using statistical thresholds, while temporal alignment harmonises measurements by aggregating high-frequency signals and interpolating low-frequency ones into fixed time windows. Spatial alignment maps each observation to the corresponding network segment using GPS data and proximity rules.

Once cleaned and aligned, datasets from subjective surveys, sensors, and infrastructural attributes are merged into a single analytical framework. This step ensures that for each segment and user, both subjective and objective variables are available, enabling cross-comparison and modelling.

2.4 Phase 4. Computation of Synthetic Indicators

Raw sensor data are transformed into synthetic indicators that summarise relevant aspects of the riding experience. Accelerometer signals are processed according to ISO 2631–1 to compute weighted Root Mean Square values representing ride comfort [3]. GPS traces yield average speeds and positional trends, while eye-tracking data produce counts of fixations and saccades that reflect attentional load [e.g., 7,16]. Biometric measures such as heart rate or skin conductance are averaged over time windows, serving as proxies for stress and exertion.

By reducing high-frequency data into interpretable metrics, these indicators allow robust comparisons across users, vehicles, and segments. They serve as objective drivers of quality, complementing the subjective ratings collected in Phase 2.

2.5 Phase 5. Predictive Modelling

The final phase develops predictive models that estimate subjective QoS from objective indicators and infrastructural variables. Two complementary approaches are applied.

The statistical approach relies on Generalised Linear Regressions (GLRs), which provide statistical interpretability and enables the identification of significant predictors. Interaction terms and transformations are included to capture non-linear effects.

The machine learning approach employs Artificial Neural Networks (ANNs), which can model complex relationships between indicators and user perceptions.

Networks are trained and validated on partitioned datasets, with model performance assessed through error metrics such as Root Mean Square Error (RMSE) and Mean Absolute Error (MAE). Feature importance is evaluated through permutation methods and sensitivity analyses.

A systematic comparison between GLRs and ANNs highlights trade-offs between interpretability and predictive accuracy. Together, the two approaches provide both explanatory insights and forecasting potential, enabling planners to identify critical factors influencing user satisfaction and to prioritise interventions.

3 Results

The methodological framework described above was applied to generate a structured dataset integrating infrastructural, subjective, and objective variables for cycling infrastructure assessment. At this stage, the research primarily focused on the methodological issues rather than exhaustive empirical testing. Therefore, results emerged in relation to theoretical implementation in terms of (i) network representation and segmentation, (ii) computation of synthetic indicators, and (iii) predictive modelling of subjective quality of service (QoS). These results provide the basis for discussing the strengths, limitations,

and implications of the proposed approach, as well as a groundwork for current empirical testing. For the sake of space available in the paper, the list of variables is reported in the Notational Glossary at the end of the paper.

3.1 Phase 1. Network Segmentation and Attribute Integration

The graph-based representation of the cycle infrastructure, segmented according to geometric, functional, and contextual discontinuities, provided the analytical foundation for data fusion. The segmentation process ensured homogeneity in both static and dynamic conditions. It is governed by two criteria:

- Statistical consistency in dynamic data distributions, such as those gathered during on-road trials (e.g., acceleration or speed traces).
- Minimum spatial resolution of available static data (e.g., slope, street category), to ensure alignment between infrastructure representation and data granularity.

As formalised in Eq. 1, the variability of dynamic indicators z within a segment was assessed through the standard deviation:

$$\sigma_{\lambda}^{(z)} = \sqrt{\frac{1}{|\Omega_s|}\sum_{\omega\in\Omega}(z_{\omega} - \overline{z_{\lambda}})^2} \tag{1}$$

A segment was considered valid if $\sigma_{\lambda}^{(z)} < \tau_z$, where τ is a tolerance threshold empirically defined. This ensured that discontinuities aligned with changes perceived by users rather than purely geometric breaks. The segmentation process is performed algorithmically, using a GIS-based procedure that applies "split" rules at each detected discontinuity.

The second preliminary activity enriched each segment with GIS attributes, creating a comprehensive dataset linking:

- Physical features, i.e., slope, width, pavement type (material), route type, dimension (width), pavement maintenance, underpass, direction, traffic volumes, road type, speed limit, bus services, node type.
- Contextual factors, i.e., tree coverage, waterscapes, protected area, landscape peculiarities, shade, historical town unit, manufacturing area, cultural peculiarity, enogastronomic peculiarity, roadside car parking, building height, building density, private vehicular access, green spaces.
- User service availability, i.e., water/drinking points, lighting, accommodation, catering, other generic shops, public transport stops/stations.

Geometries and data sources are retrieved from open and official datasets, ranging from national and regional geoportals to municipal Web Geographic Information System platforms and collaborative mapping projects (e.g., Open Street Maps). These sources often include both spatial and non-spatial components, which are reviewed and, where needed, corrected to ensure consistency with the graph structure adopted.

3.2 Phase 2. Network Segmentation and Attribute Integration

Subjective Quality of Service. User perceptions were collected through structured questionnaires during the on-road trials I. Ratings referred to multiple components Ξ (comfort, safety, ergonomics, fatigue, environment) and were aggregated into an overall quality score *y(i,λ)*. The questionnaire dataset is filled by the value *c(u)* taken by each characteristic for the user $u \in U$. Moreover, each user $u \in U$ rates the individual components that disaggregate the riding quality based on their experience during the trial. Thus, the rating associated with the overall experience during the trial $i(u,v,p) \in I$ is computed as the arithmetic mean rounded to the nearest integer of the individual components *y(i,λ,ξ)*. Specifically:

$$y(i,\lambda) = Round\left(\frac{1}{|\Xi|}\sum_{\xi\in\Xi} y(i,\lambda,\xi)\right) \forall\ i(u,v,p) \in I;\quad \forall\lambda \in \Lambda(p) \tag{2}$$

Objective synthetic indicators. An outcome was the computation of synthetic indicators summarising high-frequency sensor data.

- Accelerometer data were processed according to ISO 2631–1, which prescribes weighted RMS values for vibrations. As it is formalised in Eq. 3, the weighted RMS acceleration along axis r is:

$$m(i,acc,j,\psi) = a_j(i,acc,\psi);\ \forall i(u,v,p) \in I;\ \forall acc \in ACC; \forall j \in J; \forall \psi \in \Psi(i,acc) \tag{3}$$

- GPS data provided spatial and temporal traces (Eq. 4), and the mean speed over a time window was derived from positional differences:

$$m(i,gps,\psi) = \begin{cases} lat(i,gps,\psi)\ if\ \ q = latitude \\ lon(i,gps,\psi)\ if\ \ q = longitude \end{cases} \tag{4}$$

$$\forall i(u,v,p) \in I; \forall gps \in GPS; \forall \psi \in \Psi(i,gps)$$

- Eye-tracking data were translated into counts of fixations and saccades per window. These indicators reflect attentional load and visual scanning behaviour.fixation

$$m(i,eye,\psi) = \begin{cases} \delta_{fix}(i,eye,\psi)\ if\ \ q = state \\ x_{fix}(i,eye,\psi)\ if\ \ q = horiz.fixationcoordinate \\ y_{fix}(i,eye,\psi)\ if\ \ q = vert.fixationcoordinate \\ \delta_{sac}(i,eye,\psi)\ if\ \ q = saccadestate \\ s_{sac}(i,eye,\psi)\ if\ \ q = angularsaccadicspeed \end{cases} \tag{5}$$

$$\forall i(u,v,p) \in I; \forall eye \in EYE; \forall \psi \in \Psi(i,eye)$$

- Biometric data (heart rate, respiratory rate, skin conductance, etc.) were aggregated through mean functions, as in Eq. 6:

$$m(i, bio, q, \psi) = \begin{cases} rain(i, bio, \psi) \ if \ \ q = pulse\ rate \\ prv(i, bio, \psi) \ if \ \ q = pulse\ rate\text{variability} \\ rr(i, bio, \psi) \ if \ q = respiratory\ rate \\ sp(i, bio, \psi) \ if \ \ q = blood\ oxygen\ saturation \\ btemp(i, bio, \psi) \ if \ \ q = body\ temperature \\ eda(i, bio, \psi) \ if \ \ q = electrodermal\ activity \end{cases} \tag{6}$$

$$\forall i(u, v, p) \in I; \forall bio \in BIO; \forall \psi \in \Psi(i, bio, q)$$

These indicators provided a multidimensional and consistent description of the objective quality of service across users and contexts.

- Meteorological data

$$m(i, met, q, \psi) = \begin{cases} rain(i, met, \psi) \, if \ \ q = rain \\ temp(i, met, \psi) \, if \ \ q = temperature \\ rh(i, met, \psi) \, if \ \ q = relativehumidity \\ rad\,(i, met, \psi) \, if \ \ q = globalsolarradiation \\ wspeed\,(i, met, \psi) \, if \ q = windspeed \\ wdir(i, met, \psi) \, if \ \ q = winddirection \end{cases} \tag{7}$$

$$\forall i(u, v, p) \in I; \ \forall met \in GPS; \ \forall \psi \in \Psi(i, met)$$

3.3 Phase 3. Data Elaboration and Fusion

Next, sensor data required alignment and cleaning. Outliers were removed using the three-sigma rule (Eq. 8):

$$|m(i, s, q, \psi) - \mu(i, s, q)| > 3\sigma(i, s, q); \forall i(u, v, p) \in I; \forall s \in S; q \in Q(s); \forall \psi \in \Psi(i, s, q) \tag{8}$$

Temporal alignment was then performed by resampling all signals into fixed-duration windows (Eq. 9), applying aggregation functions for high-frequency sensors and interpolation functions for low-frequency ones.

$$syn(i, s, q, \omega) = \begin{cases} agg(\{m(i, s, q, \psi) \in M \,|\, \psi \in \Psi(i, s, q, \omega)\}) \ iff_{samp}(s) \geq 1/\cdot T \\ int(\{m(i, s, q, \psi) \in M \,|\, \psi \in \Psi(i, s, q, \omega)\}) \ iff_{samp}(s) < 1/\cdot T \end{cases};$$

$$\forall i(u, v, p) \in I; \forall s \in \mathrm{S}; \forall q \in \mathrm{Q(s)}; \forall \omega \in \Omega(i) \tag{9}$$

Spatial alignment was carried out by assigning time-window data to the nearest segmt, as formalised in Eq. 10.

$$\breve{\lambda}(i, \omega) = \underset{\lambda \in \Lambda(p)}{\arg\min}\, dist(i, \omega, \lambda); \ \forall \, i(u, v, p) \in I; \ \forall \, \omega \in \Omega(i) \tag{10}$$

This integration ensured that subjective ratings, infrastructural attributes, and synthetic indicators could be consistently merged into a unified dataset.

3.4 Phase 4. Computation of Synthetic Indicators

- Meteorological da:

$$syn(i, met, q, \omega) = m\big(i, met, q, \psi_{inf}\big) + \frac{m\big(i, met, q, \psi_{sup}\big) - m\big(i, met, q, \psi_{inf}\big)}{\psi_{sup} - \psi_{inf}} \cdot (midpoint(T(i, \omega)) - T(i, \omega)); \quad (11)$$

$$\forall i(u, v, p) \in I;\ \forall met \in MET;\ \forall q \in Q(met);\ \forall \omega \in \Omega(i);$$

- Accelerations acting along the three orthogonal axes ($j \in J$) using the multiplying factors k_j, as follows:

$$syn(i, acc, \omega) = \left(\sum_{j \in J} k_j^2 \cdot RMS^2_{(i,acc,\omega)}(i, acc, \omega)\right)^{\frac{1}{2}} \left[m/s^2\right] \quad (12)$$

$$\forall i(u, v, p) \in I;\ \forall acc \in ACC;\ \forall \omega \in \Omega(i)$$

- Eye tracking synthetic indicators:

$$syn(i, eye, \omega) = c_{fix}(i, \omega, eye), \boldsymbol{c_{sac}(i, \omega}, eye), \mu\big(x_{fix}(\boldsymbol{i}, \boldsymbol{\omega}, eye)\big), \mu\big(y_{fix}(\boldsymbol{i}, \boldsymbol{\omega}, eye)\big), \mu(s_{sac}(\boldsymbol{i}, \boldsymbol{\omega}, eye)) \quad (13)$$

$$\forall i(u, v, p) \in I;\ \forall eye \in ACC;\ \forall \omega \in \Omega(i)$$

- Biometric data

$$syn(i, bio, \omega) = \{\mu(m(i, bio, q, \omega)) : q \in Q(bio)\}; \quad \forall i(u, v, p) \in I;\ \forall bio \in BIO;\ \forall \omega \in \Omega(i); \quad (14)$$

3.5 Phase 5. Predictive Modelling

The central innovation of the framework lies in the modelling of subjective QoS as a function of objective variables. This was implemented through two alternative approaches.

According to a traditional statistical approach, GLR were applied, as formalised in Eq. 15:

$$y(\lambda, i) = GLR(\{x_h(\lambda, i)\} \in X) + \varepsilon(\lambda, i) = \alpha_0 + \sum_{x_h \in X} \sum_{\pi_h \in \Pi_h} \alpha_h \pi_h(x_h(\lambda, i)) + \sum_{(x_{h_1}, x_{h_2}) \in X \times X} \sum_{\pi_{h_1 h_2} \in \Pi_{h_1 h_2}} \alpha_{h_1 h_2} \pi_{h_1 h_2}\big(x_{h_1}(\lambda, i), x_{h_2}(\lambda, i)\big) + \varepsilon(\lambda, i);\ \forall d \in D; \quad (15)$$

According to an innovative Machine learning approach, As were implemented, following Eq. (16):

$$y(\lambda, i) = ANN(\{x_h(\lambda, i)\} \in X) + \varepsilon(\lambda, i) = \overline{\varphi}\left(\overline{u} + \sum_{\theta \in \Theta} \overline{w}(\theta) \cdot \varphi\left(u(\theta) + \sum_{x_h \in X} w(\theta, x_h) \cdot x_h(\lambda, i)\right)\right) + \varepsilon(\lambda, i); \forall d \in D; \quad (16)$$

The predictive performance of the alternative approaches was compared by Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE), while feature importance analysis was implemented to investigate the contributions of the predictors, such as vibration and slope, user characteristics (e.g., body mass, experience level), and contextual variables (e.g., shade, land use).

4 Discussion and Conclusion

The method resulted in a high level of complexity. However, segment-based representation ensures that discontinuities in infrastructure correspond to experiential differences. The combination of subjective and objective measures enhances validity, while synthetic indicators provide a manageable yet meaningful way of summarising complex signals.

From a modelling perspective, the coexistence of GLRs and ANNs offers complementary benefits: GLRs provide interpretable insights for planning and design, whereas ANNs maximise predictive accuracy and capture non-linear relationships. Overall, they establish a robust basis for both explanatory and forecasting purposes.

To conclude, the framework is implemented to supports decision-making by identifying segments with low QoS, guiding maintenance priorities and design improvements [19, 20]. However, limitations remain; the method need to be validated by empirical trial across different urban contexts and user types.

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5 Notional Glossary

Variable	Definition
U	Set of users involved in the trials
u ∈ U	A specific user
V	Set of vehicles involved in the trials
v ∈ V	A specific vehicle
P	Set of paths used in the trials

(*continued*)

(*continued*)

Variable	Definition
$p \in P$	A specific path
$\Lambda(p)$	Set of segments along path p
$\lambda \in \Lambda(p)$	A specific segment
I	Set of trials
$i(u,v,p) \in I$	A trial *i*, performed by user u with vehicle v on path p
Ξ	Set of subjective quality components (comfort, safety, ergonomics, fatigue, environment)
ξ	A specific rating component
$y(i,\lambda,\xi)$	Rating for component ξ during trial i on segment λ
$y(i,\lambda)$	Overall quality rating for segment λ during trial i
L	Set of rating levels (e.g., 1–5 or qualitative labels)
ACC	Set of accelerometers used in trials
J	Set of Cartesian axes (e.g., x, y, z)
$a_j(i,acc,\psi)$	Acceleration along axis j at time ψ during trial i
GPS	Set of GPS devices used in trials
$lat(i,gps,\psi)$	Latitude at time ψ during trial i
$lon(i,gps,\psi)$	Longitude at time ψ during trial i
EYE	Set of eye-tracking devices used in trials
$\delta_fix(i,eye,\psi)$	Binary indicator of fixation state at time ψ
$x_fix(i,eye,\psi)$	Horizontal fixation coordinate
$y_fix(i,eye,\psi)$	Vertical fixation coordinate
$\delta_sac(i,eye,\psi)$	Binary indicator of saccade state
$s_sac(i,eye,\psi)$	Angular saccadic speed
BIO	Set of biometric sensors used in trials
$pr(i,bio,\psi)$	Pulse rate
$prv(i,bio,\psi)$	Pulse rate variability
$rr(i,bio,\psi)$	Respiratory rate
$sp(i,bio,\psi)$	Blood oxygen saturation
$btemp(i,bio,\psi)$	Body temperature
$eda(i,bio,\psi)$	Electrodermal activity
MET	Set of meteorological stations
$rain(i,met,\psi)$	Rainfall
$temp(i,met,\psi)$	Temperature
$rh(i,met,\psi)$	Relative humidity

(*continued*)

(*continued*)

Variable	Definition
rad(i,met,ψ)	Solar radiation
wspeed(i,met,ψ)	Wind speed
wdir(i,met,ψ)	Wind direction
σ_λ(z)	Standard deviation of indicator z within segment λ
τ_z	Tolerance threshold for indicator z
m(i,s,q,ψ)	Raw measurement of quantity q from sensor s at time ψ
μ(i,s,q)	Mean of quantity q from sensor s during trial i
σ(i,s,q)	Standard deviation of quantity q from sensor s during trial i
syn(i,s,q,ω)	Synthetic indicator for sensor s and quantity q in time window ω
ω ∈ Ω(i)	Time window ω in trial i
ĉλ(i,ω)	Segment assigned to time window ω
x_h(λ,i)	Predictor h for segment λ during trial i
y(λ,i)	Predicted subjective quality of service
ε(λ,i)	Residual error of prediction
GLR(x_h)	Generalised Linear Regression model
ANN(x_h)	Artificial Neural Network model

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