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Exploring free riding behavior: An instrumented bicycle study on the impact of infrastructure and wind on bicycling

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ABSTRACT

Understanding free riding behavior—where bicyclists are unconstrained by other road users or traffic control measures—is essential for planning efficient and appealing bicycle traffic systems. Bicyclist behavior is shaped by a combination of environmental conditions and individual preferences. This study examines free riding behavior, and identifies correlations with individual characteristics and contextual features such as infrastructure design (slopes and curves) and wind speed. We introduce a method using instrumented bicycles in a semi-controlled experiment to collect data describing the speed, power output, and heart rate of commuting bicyclists. Participants in two study populations (28 in Sweden and 29 in Germany) ride their bicycles equipped with sensors along designated routes during off-peak demand periods, enabling comparative analysis of different trip features. Results highlight significant inter- and intrapersonal variations in speed and power output along a trip. Approximately 80 percent of the variation in free riding speed and power output over a trip, and over both populations of bicyclists, is explained by gender, individual preferences, topography, curvature, crossing intersections, and wind speeds. Headwinds and uphills generally reduce speeds but bicyclists increase power output to partially offset these effects. Downhills lead to high speed variation and distinct tactical behaviors, such as braking, coasting, and accelerating. These findings underscore the complexity of bicycling behavior and quantify how bicyclists adapt to varying features of the trip.

1. Introduction

The built environment plays a vital role in encouraging or deterring bicycling (Heinen et al., 2010; Pucher et al., 2010; Winters et al., 2010). Bicyclists engage with the built environment in multifaceted ways, and the broad diversity in their preferences and characteristics further shapes how they perceive and respond to their surroundings (Habib et al., 2024). Understanding the complexity of bicyclist behavior is crucial for planning efficient and safe transportation systems. For example, designing bridges or parking garage entrances for bicyclists requires understanding acceptable gradients that balance efficiency and effort across diverse bicyclists. Assessing traffic safety at intersections could benefit from accurate estimations of bicyclist speeds on downhill approaches, as higher speeds elevate conflict risks. Estimating energy expenditure and travel time on bicycling routes also requires accurate modeling of bicyclist responses to the built environment. Such knowledge is presently limited, hindering evidence-based planning for safe and attractive bicycle infrastructure.

Free riding behavior, where bicyclists are uninfluenced by other road users or traffic control measures, such as traffic lights, is key for understanding bicycle traffic dynamics. It reflects the properties of the bicycle, individual preferences, as well as physical capabilities and perceptions of effort, both of which are particularly relevant in human-powered transportation (Twaddle and Grigoropoulos, 2016; Bigazzi and Lindsey, 2019; Raffler et al., 2019). As a result, free riding varies greatly. These individual characteristics, in combination with infrastructure design and weather conditions, ultimately shape the speed choices of bicyclists.

Speed is a fundamental aspect of bicycle traffic directly connected to efficiency and user experience. Pérez Castro et al. (2025) summarized findings from the literature, highlighting that speed varies with age, gender, bicycle type, and trip purpose, alongside contextual factors such as trip length, rush hour periods, type of infrastructure, and access to shower facilities. Bicyclists also employ specific tactics to navigate curves, with their strategies differing depending on traveling

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speed (Vansteenkiste et al., 2014). Furthermore, the effects of topography on speed have been explored in Parkin and Rotheram (2010), Flügel et al. (2019), Romanillos and Gutiérrez (2020) and Pérez Castro et al. (2023). While aerodynamic resistance is the largest force bicyclists encounter on flat terrain (Wilson et al., 2020), its impact on speed is not always significant when commuting. For instance, light tailwinds (up to 5.5 m/s) have been shown to increase the speed of bicyclists, whereas headwinds of the same magnitude had no notable effect (Yan et al., 2024). Moreover, Pérez Castro et al. (2025) reported no significant effects on speeds for winds up to ±3 m/s in video-based trajectory analyses combined with independent wind measurements near the bicycle path. Based on a large GPS-trajectory data set, Yan et al. (2024) explained speed variance in bicycle traffic across three levels: 30% is attributed to differences between bicyclists, 21% to variation between trips of the same bicyclist, and 49% to differences within individual trips. Similarly, Maurer et al. (2025) used a large GPS-trajectory dataset to reveal significant speed variations primarily influenced by gradients, BMI, age, and type of bicycle. Bicycle type, in particular, has been identified as having the greatest effect on free-flow speed according to Yan et al. (2020). Despite extensive research on speed, many studies rely on data where it is unclear whether observed speeds are influenced by other road users, and to what extent those observations reflect preferred free riding speeds.

Bigazzi and Lindsey (2019) described speed choices as trade-offs between travel time, energy expenditure, and stability control. For instance, bicyclists tend to choose higher speeds when using electrically assisted bicycles, indicating that energy expenditure is pivotal in speed choice (Mohamed and Bigazzi, 2019). Power output may serve as a proxy metric for energy expenditure in bicycling, offering an objective measure that is often easier to quantify than energy use or subjective effort. Power output, as well as heart rate, is closely associated with oxygen uptake, and thus, enabling direct estimation of energy expenditure (Bigazzi and Figliozzi, 2015; Salier Eriksson et al., 2021). Previous studies have shown a significant reduction in power output with electric support (Matyja et al., 2022b), and that power output varies notably with gradients (Parkin and Rotheram, 2010; Kunert et al., 2021; Pérez Castro et al., 2023); e.g., steeper uphill gradients generally lead to higher power output. Despite its importance, research on power output in utilitarian trips remains limited, with most studies relying on speed-based estimates of power output, as in Parkin and Rotheram (2010), Mohamed and Bigazzi (2018) and Pérez Castro et al. (2023).

Quantification of bicycling behavior often relies on methods for video analysis and GPS tracking, which are often limited to capturing data associated with gradual environmental changes. Video analysis captures interactions with other road users and infrastructure but is labor-intensive and location-specific. GPS tracking offers extensive floating data but lacks the granularity and accuracy to capture effort and bicycling dynamics or detailed environmental context (Lißner and Huber, 2021), such as traffic and infrastructure, requiring integration with other data sources. To address these limitations, instrumented bicycles (IBs) equipped with various sensors have been introduced as a comprehensive data collection method (Matyja et al., 2022a). IBs record detailed user-specific trajectory data of e.g., speed, cadence, heart rate, and power output, while also capturing the environmental context around bicyclists. A review by Gadsby and Watkins (2020) highlighted that sensor choices in IBs depend on study objectives, and stressed the need for standardized instrumentation for better comparability and reproducibility. Other challenges include the complexity of sensor instrumentation, or designing a suitable experiment for data collection, as highlighted by Kircher et al. (2017).

Much research using IBs has focused on safety, using advanced, often custom-built, sensors that capture detailed data on conflicts and risky behavior. For instance, detailed dynamics on braking and lateral movements have been documented (Dozza and Fernandez, 2014; Huertas-Leyva et al., 2018), drawing on relatively small samples of bicyclists but extensive trip data per participant. Comfort zones during obstacle avoidance maneuvers have been modeled by Lee et al. (2020), while mental workload in urban traffic has been investigated using simpler setups focused on heart rate measurements, as by Pejhan et al. (2021). These studies frequently face data synchronization and cost challenges, as highlighted by Duran Bernardes and Ozbay (2023), who addressed these issues by integrating multiple sensors into a single data acquisition system. Extensive data collection and processing may also limit the number of participants in a study. Additionally, the limited portability of advanced instrumentation often translates to using a single IB for all participants, potentially influencing naturalistic behavior.

Other research using IBs has focused on performance, primarily examining efficiency and comfort. For example, delays at intersections with motorized traffic were analyzed concerning priority rules and bicyclist characteristics, showing that delays varied across bicyclist types (Kircher et al., 2018); faster bicyclists faced greater delays at mandatory stops, while comfort-oriented bicyclists were most delayed at mixed-traffic roundabouts. Matos et al. (2021) estimated travel times and energy expenditure for various bicycling routes using a single IB equipped with GPS and a heart rate sensor. Systematic changes in pedaling were reported as an adaptive response to changes in elevation in Kunert et al. (2021). Gradients and surface quality have been observed to affect speed and perceived comfort, with effects varying by experience level according to Feizi et al. (2020). Additionally, Zhu and Zhu (2019) found road surface, together with lane width and separation from pedestrians, as a significant factor influencing comfort. Using a range of methods, such as crowd-sourced GPS data, accelerometers, or smartphone-mounted sensors, other studies have also demonstrated that smoother surfaces improve travel speed and comfort, and yield substantial societal and user-level benefits through better infrastructure maintenance and planning (Argyros et al., 2024; Ahmed et al., 2023; Cafiso et al., 2022). Lastly, aggregated analysis by Shoman et al. (2023) showed significant speed and power output reductions on snowy surfaces compared to dry conditions. Performance studies highlight the impact of infrastructure on bicycling behavior, with effects varying notably across bicyclists. However, performance studies have rarely measured power output in utilitarian trips, aside from aggregated results in Shoman et al. (2023), and seldom allow participants to use their bicycles, with Kircher et al. (2018) being a notable exception.

While IB studies have provided valuable insights into bicycle traffic performance, comprehensive datasets capturing diverse free riding behavior under various contexts are still lacking. By collecting detailed trajectory data on free riding behavior, including power output measurements, and allowing participants to use their own (non-electric) bicycles, the objective of this study is to characterize the speed and power output across two populations of commuting bicyclists. Additionally, we investigate heart rates as a supplementary measure to gain further insights into bicyclist behavior. We describe how these behaviors vary among bicyclists and identify correlations with demographics and contextual features, such as infrastructure design (namely horizontal and vertical alignment) and wind.

Understanding the speed dynamics, physical exertion, and related tactical behaviors in bicycle traffic can inform better traffic and infrastructure planning, model development for the simulation of bicycle traffic, and optimization techniques for e-bike motor assistance that guarantee adequate support in difficult terrain. Moreover, detailed characterization of power output in bicycle traffic can provide the basis for incorporating energy expenditure into traffic modeling and inform route and mode choice decisions.

2. Methods

We describe the methods used in this study, divided into four subsections. First, we outline the experimental design, including the recruitment process, bicycle instrumentation, and instructions to participants. Second, we introduce data acquisition and processing procedures, followed by the methods used to characterize behavior, and a description of the study locations.

2.1. Experimental design

To measure free riding behavior, we recruit people to participate in a semi-controlled experiment using IBs. We adopt a semi-controlled experimental design to investigate operational and tactical behavior. The experiment encompasses six stages:

Recruitment of participants. We aim to collect data from frequent commuters who ride conventional bicycles at least 2–4 times per week. No e-bikes are included in this study as we focus on behavior without electric support. We recruit participants through social media, community boards, and flyers. During this stage, we collect background information on potential participants, such as age, gender, and bicycling experience and habits.

Documentation of individual characteristics. We register the characteristics of the participants and their bicycles that are relevant to analyzing bicycling dynamics and behavior. Individual characteristics include the total weight of the bicycle and the participant, including accessories worn while bicycling (bags, helmet, etc.), the type of bicycle (e.g., commuter, road, mountain, etc.), mechanical properties of the bicycle (type of brakes and gearing system), and bicycle dimensions (length, width, and tire size).

Instrumentation of bicycle. We install various sensors on the participants and their bicycles to collect information about their behavior and the environment. These devices do not add significant weight to the bicycle and are unobtrusive. Complete instrumentation of a bicycle takes approximately 10 min. A bicycle is provided if the participant's bicycle cannot be instrumented (e.g., the original pedals cannot be removed); in such situations, participants choose from various bicycles, featuring distinct frame designs (diamond or step-through) and wheel sizes, to find the most suitable option for their comfort.

Data acquisition. We collect trajectory data from each participant during one trip along a designated route. Participants are instructed to ride at their preferred pace as they would during a typical commuting trip; the research team neither impose restrictions, nor encourage specific behaviors, and avoid interaction with participants during the trip. To facilitate the identification of free riding, participants are further instructed to communicate whenever they feel another road user constrains their speed. We schedule rides outside peak hours, between 9:00 and 16:00, to reduce interactions with other road users. Routes are chosen to ensure that participants experience a range of gradients, curvatures, and wind exposures. Furthermore, we select routes that are easy to follow; temporary signs (see Fig. 2) are placed along the route to guide participants. Lastly, we document weather and traffic conditions for each trip.

Post-ride. After completing the trip, participants provide feedback on prior familiarity with the route, indicating if it is frequently used or entirely unfamiliar to them, and whether they experience any issues with the equipment or following the route, including whether these issues influence their behavior. The purpose of collecting this contextual data is to control for potential impacts of the experimental setup on the observed behavior.

2.2. Data acquisition and processing

We use commercially available devices to equip the bicycles. The main component of our data acquisition setup is a bicycle computer with onboard memory for data logging, gathering data at a frequency

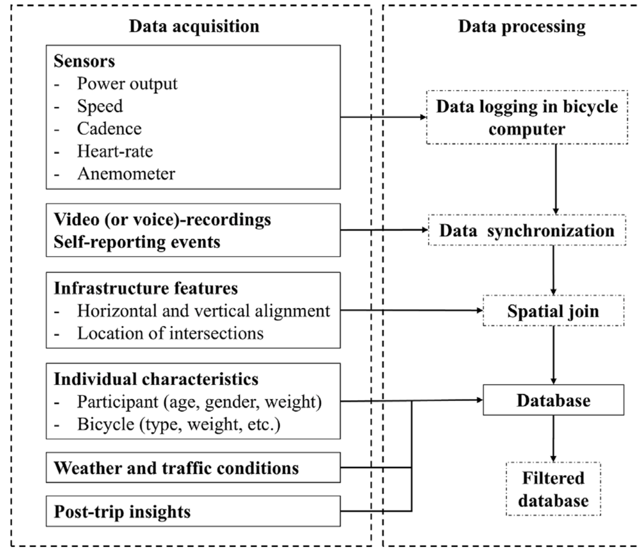

Fig. 1. Overview of data acquisition and processing.

of 1 Hz. A key criterion in sensor selection is the ease of installation, ensuring that the equipment can be quickly and easily transferred between bicycles. Table 1 summarizes the components used in this study, along with their manufacturers, primary function, and installation location on the bicycle.

The bicycle instrumentation includes sensors for measuring bicyclist behavior, such as speed, cadence, power output, and heart rate. Power measurements indicate pedaling activity when positive, while zero readings may indicate coasting or braking. Braking with coaster brakes (if available) does not produce false pedaling measurements, as forward pedal rotation is required for positive power readings. To gather contextual information, we complement the instrumentation with video/audio recorders, an event button, and an anemometer. While video recordings are useful for capturing the environment around the participants, audio recordings and the event button allow participants to self-report instances of constrained behavior. The anemometer collects wind speed data throughout the trip; Kordi et al. (2022) and Millour et al. (2022) showed that wind speed, as measured by Notio, can be used to estimate aerodynamic drag and power output accurately. Although both the bicycle computer and the anemometer track GPS coordinates independently, only the location data from the bicycle computer is used in the analysis, as it consistently tracks more accurate and stable positioning.

The data acquisition and processing workflow is summarized in Fig. 1. The process starts with automatically logging and synchronizing the sensor data (including wind speed data) in the bicycle computer, establishing a centralized repository for information with associated GPS coordinates. Video/audio recordings and self-reported events are time-based and paired with the sensor data after collection. Infrastructure features are sourced from ground elevation models with a 1-m resolution (Lantmäteriet, 2021; Geschäftsstelle IMA GDI.NRW, 2024). The Point Sampling Tool (Jurgiel, 2022) is a GIS utility that extracts attribute values (such as elevation data) from a raster dataset for each point in a vector dataset (such as our trajectory point measurements). GPS coordinates often align well with infrastructure, typically within 2 m and mostly parallel to the route, allowing a simple spatial join using the nearest point algorithm (GeoPandas Development Team, 2021) to synchronize sensor data to the route. When alignment is poor, we manually adjust trajectory coordinates before proceeding with the map-matching.

For each participant, we store a detailed logbook that includes their personal and bicycle characteristics, sensor data (joined with video/audio recordings and infrastructure features), post-trip insights,

Table 1
Hardware components.

Component	Function	Manufacturer and model	Installation location
Bicycle computer	Data logger/GPS tracker	Garmin Edge 1040	Handlebar
Power-meter pedals	Measurement	Garmin Rally XC200/Favero Assioma	Pedals
Speed sensor	Measurement	Garmin Bundle2	Wheel hub
Cadence sensor	Measurement	Garmin Bundle2	Crank arm
Heart-rate monitor	Measurement	Polar Veridity Sense	Arm of participant
Event-button	Measurement	In-house manufactured	Handlebar
Anemometer	Measurement/GPS tracker	Notio	Handlebar
Microphone	Audio recorder	DJI Mic 2	Chest of participant
Video camera	Video recorder	Sony FDR-X3000/GoPro Hero 10	Handlebar

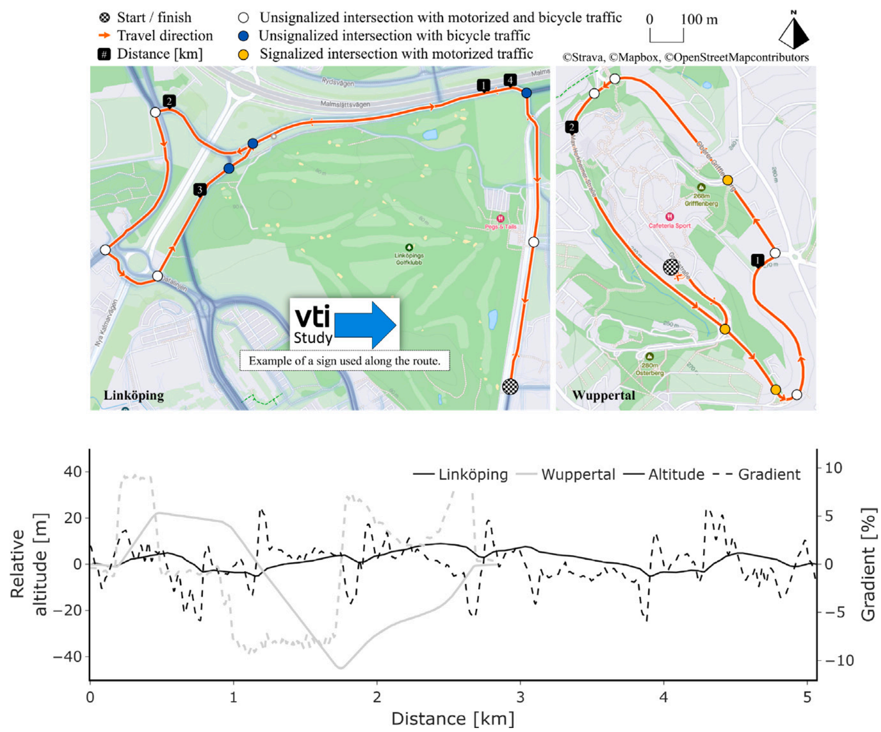

Fig. 2. Travel routes for experiment in Linköping and Wuppertal. Note: Altitude relative to the start of the route.

and contextual information on weather and traffic conditions during the experiment. In this paper, we analyze records from participants who report no impact on their riding behavior from the instrumentation or the borrowed bicycle (if relevant).

To reduce measurement noise in speed and power output, we apply a rolling window averaging algorithm with a window size of three observations. Constrained behavior, i.e., influenced by other road users or traffic signals, is identified through video analysis, using participants' self-reported events to locate relevant segments. We annotate events such as overtaking, potential following, crossings with other road users, and stopping due to red signals at intersections. We define the start of each constrained behavior at the first noticeable drop or irregularity in speed associated with the event, and the end when speed returns to pre-constraint levels, adding a buffer (ranging from 5 to 30 s) to mitigate lingering effects; buffer length depends both on the speed and infrastructure, for instance, effects may be prolonged on downhill sections. Constrained behavior is filtered out from the analysis, ensuring that only data representing free riding behavior are used for further examination. Additionally, instances in the trajectory data where participants report being significantly confused while following the route are identified and excluded from the analysis.

2.3. Data analysis

We define bicycling preferences in terms of speed and power output. Preferred (desired) speed is an important metric for understanding the delays bicyclists face along their routes, whether caused by other road users or the infrastructure. We estimate the preferred speeds as the observed speeds at straight, flat, low-wind segments when the participants are free from the influence of other road users or traffic signals. The preferred power output corresponds to the observed power when traveling at the preferred speed. Thereby, we observe preferred speed and power on straight segments with gradients up to $\pm 1\%$, excluding measurements when wind speeds exceed 3 m/s in magnitude. To account for the physiological response lag in heart rate data, we find the lag that maximizes the correlation between the heart rate and power output.

We use Spearman's rank correlation to identify relationships between bicyclist characteristics and preferences. Moreover, we apply a two-level mixed-effects modeling framework to analyze the relationship between behavior (speed and power output) and contextual factors: demographics, infrastructure design, and wind. This framework is well-suited to our trajectory data, which consists of several observations over time for each participant. The model accounts for the hierarchical structure of the data, with observations along the trajectory at level 1 and bicyclists at level 2, modeling both population-level effects and individual-specific variations. Mixed-effects models account for both fixed effects, which influence all participants (e.g., environmental factors), and random effects, which capture individual-specific variability in responses to predictors. The general form of the mixed-effects models can be expressed as:

$$y_{ij} = \beta_0 + \sum_{k=1}^{p} \beta_k x_{ijk} + u_{0j} + \sum_{k=1}^{q} u_{kj} x_{ijk} + \epsilon_{ij}, \tag{1}$$

where y_{ij} is the dependent variable (speed or power output) for observation i (level 1) in bicyclist j (level 2), β_0 is the fixed intercept, β_k are the fixed-effect coefficients for predictors x_{ijk} (e.g., gradient, wind speed, etc.), u_{0j} are the individual intercepts, capturing the deviations specific to bicyclist j, u_{kj} are the individual responses for predictors x_{ijk}, allowing their effects to vary among bicyclists, and ϵ_{ij} is the residual error term, assumed to follow $\mathcal{N}(0, \sigma^2)$. We fit linear mixed-effects models using the "MixedLM" function from the "statsmodels" package in Python (Skipper and Josef, 2010).

2.4. Case study

The experiment is conducted in two locations: Linköping, Sweden, and Wuppertal, Germany, differing mainly in their topography and infrastructure design Linköping is relatively flat with bicycle paths separated from motorized traffic, while Wuppertal has steep hills and lacks dedicated bicycle infrastructure.

In Linköping, participants are selected primarily based on bicycling frequency for commuting (at least 2–4 times per week, all year round), and self-perceived commuting style, categorized as fast, moderate, or relaxed commuters. The purpose of this criteria is to ensure an even distribution across commuting styles. In Wuppertal, we select a population of frequent bicycle commuters who are fit enough to handle the difficult topography of the route. Therefore, potential participants are asked to assess their fitness level from non-athletic to athletic. Additional criteria in both locations include being between 18 and 65 years old and being able to bring their bicycle. A total of 28 and 29 participants join the experiments in Linköping and Wuppertal, respectively. A 300 SEK incentive is provided to promote participation in Linköping, while no incentives are provided in Wuppertal.

In both experiments, we use the same models of bicycle computers and sensors for speed, cadence, and heart rate, along with similar models for power-meter pedals and video recording. The anemometer is implemented only in Linköping, since Wuppertal lies in a wind-protected valley where the strong effects of steep road gradients greatly outweigh the effects of wind speed on bicycling behavior. Moreover, the identification of constrained behavior is supported by the event button and video in Linköping, and by video and audio in Wuppertal.

The Linköping route is 5 km long, entirely separated from motorized traffic (see Fig. 2), and following a semi-circuit loop formed by two distinct sections: one traveled twice (back and forth); the other traveled only once. The route features light to moderate hills (gradients up to $\pm 6\%$), seven flat segments, and intersects with bicycle traffic at eight locations, and with motorized traffic at four unsignalized intersections (where bicycles have priority). In contrast, the Wuppertal route is 3.2 km long and runs in mixed traffic (no dedicated bicycle lanes), following a closed loop around the university campus. The route features moderate to steep hills (gradients up to $\pm 13\%$), including three flat segments, one steep ascent, one prolonged and steep climb, and one continuous downhill section. Additionally, the route includes three signalized intersections (one of which is passed twice) and low motorized traffic flows. The busiest street along the Wuppertal route carries approximately 6000 vehicles per day, with approximately 600 vehicles/hour during peak demand periods. Since data collection occurs during off-peak periods, motorized traffic volumes are low, and interactions with motor vehicles are infrequent, allowing bicyclists to use the available space with minimal restrictions. The surface quality on both routes is generally acceptable and consistent; this assessment is based on visual inspection of video recordings and participant feedback.

Data collection takes place during autumn 2023 (October/November) in Linköping, and during summer 2023 (June) in Wuppertal. In Linköping, temperatures range from 0 to 12.5 degrees Celsius, and wind speeds (recorded by anemometer) range between ± 6 m/s in the travel direction; negative values indicate tailwinds, positive values headwinds. In Wuppertal, temperatures range from 18 to 30 degrees Celsius (Deutscher Wetterdienst, 2024), and wind speeds up to 3 m/s in magnitude are recorded at the weather station four kilometers from the experiment site. Since an anemometer is not used to measure local wind speeds in Wuppertal, weather station data may differ from site conditions due to distance and wind obstructions. However, based on experiment reports in Wuppertal, wind sensation is negligible on site. The seasonal difference between the two locations results in variations in the clothing worn by participants, affecting their total weight and aerodynamic resistance. No intense sunlight is documented during the experiments, and no participants report discomfort from temperature or glare.

3. Results

Data analysis of the two populations (Linköping and Wuppertal) is presented in this section. First, we provide an overview of the characteristics of the participants. Next, we examine the influence of two infrastructure design features—vertical and horizontal alignment—and wind speeds on speed, power output, and heart rate. Finally, we analyze bicycling preferences (speed and power output) and their relationships with infrastructure design and wind.

3.1. Characteristics of participants

In Fig. 3, we present the distributions of age, gender, and type of bicycle. The age distribution reveals a younger population in Wuppertal compared to Linköping, which can be attributed to the prerequisite of physical fitness in recruitment. In contrast, Linköping has participants from a wide range of age groups. The majority of participants are men in both populations, with women making up approximately 21% of the combined samples. While we find no specific studies that detail the share of women in bicycle traffic in Germany or Sweden, international surveys showed that in areas with bicycling mode shares below 7%, women cycle less than men (Goel et al., 2022). The total weights of participants, including their bicycles and any additional gear, are relatively similar in both locations, with a mean of 101.5 kg (std. deviation: 12.9 kg) in Linköping and 98.2 kg (std. deviation: 11 kg) in Wuppertal. Minor weight differences may reflect variations in age and clothing between the two populations; the latter due to seasonal differences in data collection. In Linköping, participants predominantly use city/commuter bicycles, while in Wuppertal, the distribution of bicycle types is more diverse, including mountain bicycles (MTBs) and race/road bicycles; because of restrictions in sensor installation, nine participants use a bicycle other than their own.

The selected route in Linköping is not part of the usual commuting route for 85% of the participants. However, 71% are familiar with the area where the experiment takes place. Due to the experimental design, four participants in Linköping report being confused when turning at one of the intersections; these specific trajectory segments are excluded from the analysis. In Wuppertal, all participants are familiar with the selected route, as the participants are mainly associated with the university campus. Self-perceptions of commuting style in Linköping are split between fast (57.1%) and moderate (42.9%) commuters, with no participants identifying as relaxed commuters. In Wuppertal, self-perceptions indicate a population with relatively good physical fitness, with 51.7% identifying as athletic, 34.5% as average, and 13.8% as unathletic.

We use the average number of interactions per kilometer as a proxy for the surrounding traffic, since precise traffic flow data are unavailable. Interactions with road users or traffic signals occur, on average, every 2 km in Linköping, and every 1.5 km in Wuppertal. The filtering process for constrained behavior excludes 3.7% and 17.2% of all time-based trajectory observations (i.e., data points recorded per

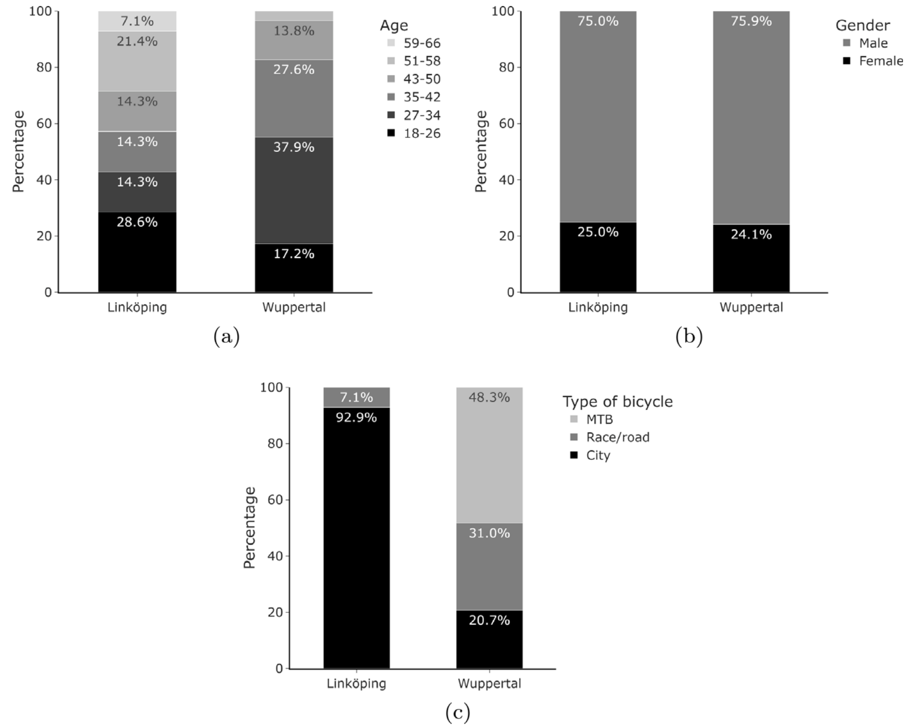

Fig. 3. Distributions of (a) age, (b) gender, and (c) type of bicycle of participants.

second) in Linköping and Wuppertal, respectively. The higher exclusion rate in Wuppertal reflects data removal at signalized intersections, where some bicyclists wait at red lights. In terms of distance traveled along the route, the filtering corresponds to 3.6% of the total trajectory length in Linköping and 8.9% in Wuppertal.

3.2. Impact of infrastructure design

Vertical alignment. The vertical alignment (gradients) has a significant influence on bicyclist behavior. Fig. 4 illustrates the impact of longitudinal gradients on speed, power output, and heart rate. Speeds generally decrease with increasing gradients, from negative (downhill) to positive (uphill) gradients. The distribution of speeds widens significantly on the steepest downhills. The highest speeds observed may result from a combination of local steep gradients and the distance traveled since the start of the descent.

On uphills, power output increases as gradients increase, eventually reaching a plateau. This suggests that participants are approaching the upper limit of their ability or desire to generate additional power. Heart rate data also displays an upward trend with increasing uphill gradients, reflecting the greater physical effort during uphill bicycling. In contrast, power output approaches zero as the downhills get steeper, indicating evident coasting or braking on steeper descents. Heart rate does not seem to be influenced by downhill gradients.

Perceptions of effort may lead to different tactics to manage physical exhaustion. Therefore, we analyze the power output trajectories of participants in two situations in which tactical behavior may occur: (1) transitioning from a downhill to an uphill; and (2) based on the length of the uphill segment, i.e., examining whether behavior changes during a long ascent. Fig. 5 illustrates data from Linköping, showing a transition from downhill to uphill. This route segment is familiar to all participants, as they have already traveled it once, although in the opposite direction. Participants also have good visibility of the upcoming uphill. In this situation, the power output data suggest two distinct tactics for coping with the uphill. Tactic 1 (in blue) depicts a sustained low or zero power output during the downhill, which then increases during the uphill. In contrast, tactic 2 (red) exhibits a notable surge in power output before the uphill. While tactic 1 reflects coasting behavior on the downhill, tactic 2 increases power output to boost speed. With the downhill assistance, participants who take tactic 2 have a smoother increase in power when transitioning uphill. The distinct tactics are also evident in similar downhill–uphill transitions with good visibility along the route or where participants travel twice.

In Wuppertal, the route also includes a transition from downhill to uphill, but with the distinction that these sections are longer and steeper. Fig. 6 shows the progression of power output on the uphill section of this transition. Overall, the power output profiles indicate low values at the beginning of uphill, followed by a peak within the first 100 m due to the rapid increase in the gradient of the climb. After this peak, however, the behavior diverges into two distinct types (tactics). Tactic 1 (blue) represents participants with generally low power output who maintain a relatively constant power output towards the end of the climb. In contrast, tactic 2 (red) represents participants whose power output varies in response to the gradient throughout the climb.

Horizontal alignment. In Linköping, where the lateral available space is more restrictive, the results demonstrate a clear relationship between curvature and speed (see Fig. 7). Speeds decrease with increasing curvature, with sharp curves reducing speed, in average, by approximately 35% compared to straight segments. However, neither power output nor heart rate shows a clear trend in these conditions.

In Wuppertal, participants ride on street roads with large-radius curves, allowing enough space for maneuvering results in minor speed reductions through the curves.

3.3. Impact of wind

Analysis of wind speed effects is only conducted for Linköping, where we have detailed wind speed data. In Fig. 8, we show that strong headwinds result in a decrease in speed while also leading to an increase in power output. Heart rate shows a slight inclination to rise as headwind intensity increases, as indicated by the median.

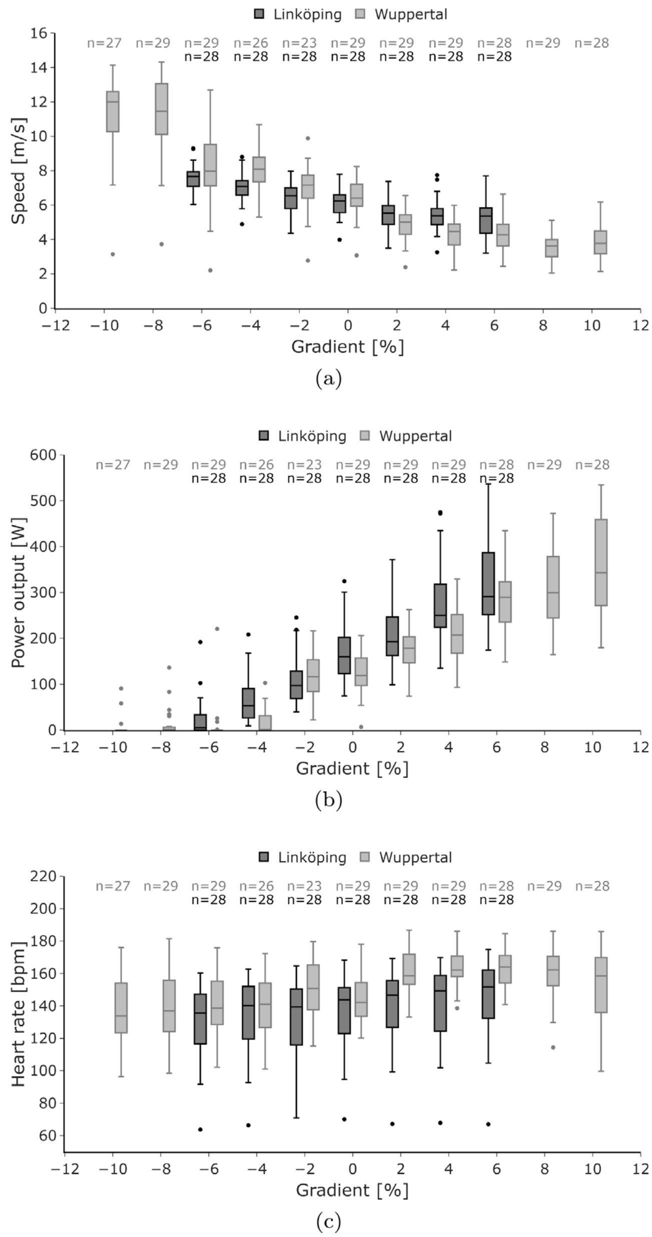

Fig. 4. Impact of longitudinal gradients on (a) speed, (b) power output, and (c) heart rate. Note: the analysis includes observations from straight segments with low wind speeds.

3.4. Bicycling preferences

We identify seven segments in Linköping and three in Wuppertal where we estimate preferred (desired) speeds and power outputs, as defined in Section 2.3.

In Fig. 9, we show the distribution of preferred speeds and power outputs of participants, averaged over all selected segments. A Kolmogorov–Smirnov (KS) test, with a 95% confidence level, confirms that the distributions of preferred speeds are statistically similar between Linköping and Wuppertal (p-value = 0.110 and KS-statistic = 0.302). However, the KS test for power outputs indicates a significant difference between the two locations (p-value = 0.017 and KS-statistic = 0.397). Even though preferred speeds are similar in both locations, these speeds do not necessarily correspond to the same power output levels (also evident in Fig. 4(b) for each gradient). The difference in power outputs is likely due to significant differences in wind resistance, as participants in Linköping face stronger headwinds and wear bulkier clothing (further increasing their aerodynamic resistance), ultimately requiring a higher propulsive force to maintain the desired speed.

In Fig. 10, we present the distribution of average preferred speeds of participants for each segment. Note that the analyzed segments are not consecutive, and the sample sizes are reduced since we require measurements in all selected segments. In both locations, there is noticeable variability between the speed and power output distributions throughout the trip. In Linköping, these differences are likely influenced by the presence of hills between segments, which have a lasting effect on speed and power output. For example, speeds at the fifth segment (km 3.7) are potentially influenced by a preceding light but long downhill. In Wuppertal, speeds and power outputs appear to decrease over time but may also be influenced by preceding conditions. The last speed measurement is taken on a segment that follows a long and steep uphill.

A power curve represents the maximum power output a bicyclist sustains over time. In Fig. 11, the observed power curves of participants range from 2 to 8 W/kg over 1 s. While power curves are commonly employed to determine the peak abilities of sports bicyclists, the observed power output in this study reflects the maximum bicyclists are willing to exert during typical commuting trips. Moreover, the power curves stay relatively stable over 5 min for both locations. Although the power curves of the two populations overlap substantially, the median power output in Wuppertal is notably higher than in Linköping. The difference is expected due to the topography in Wuppertal and the higher physical fitness of its participants. Despite the overlap, differences in the distribution of the power curves underscore variations in performance preferences (and capabilities) between the two populations.

The matrix presented in Fig. 12 shows Spearman's rank correlation coefficients (ρ) between individual characteristics, and bicycling preferences and tactics for both locations. Male participants generally ride faster than female participants ($\rho = 0.52$), regardless of horizontal and vertical alignment, also generating slightly more power output ($\rho = 0.43$). No significant correlation is found between age and speed. However, older participants may identify with a moderate commuting style compared to younger participants, indicated by lower heart rate measurements with age ($\rho = -0.22$), suggesting a decrease in physical exertion. Total weight is correlated only with power output ($\rho = 0.44$).

Men are also more inclined to adopt a boosting-speed tactic to cope with uphills ($\rho = 0.5$); an analogous pattern is noted among race-bike users. Bicyclists using this tactic also exhibit positive correlations with both speed ($\rho = 0.39$) and power output ($\rho = 0.32$). On long uphills, no significant correlation with gender is observed, but a correlation with age ($\rho = -0.49$) suggests that younger participants are more likely to adopt an adaptive tactic throughout the climb, possibly reflecting their higher physical fitness. The gradient-adaptive profile also correlates with weight ($\rho = 0.49$), likely reflecting increased power capabilities associated with higher body mass. Findings are largely consistent between Linköping and Wuppertal, except for the correlation between age and power output. Age is negatively correlated with power output in Linköping but the opposite in Wuppertal, likely due to the narrower age distribution in the Wuppertal population.

3.5. Mixed-effects modeling for bicycling behavior

Mixed-effects models for speed and power output are developed for three datasets: Linköping, Wuppertal, and a combined dataset. The results of the six models are , summarized in Table 2.

The intercepts represent the baseline bicycling behavior when all predictors are zero. Baseline speeds are slightly higher in Linköping (5.50 m/s) than in Wuppertal (5.27 m/s). The baseline power output is approximately 40 W higher in Linköping. The random intercepts reveal the variability among bicyclists (illustrated in Fig. 13), with a standard deviation going from 0.710 m/s (Wuppertal) to 0.749 m/s (Linköping) for speed and from 29.798 W (Wuppertal) to 59.343 W

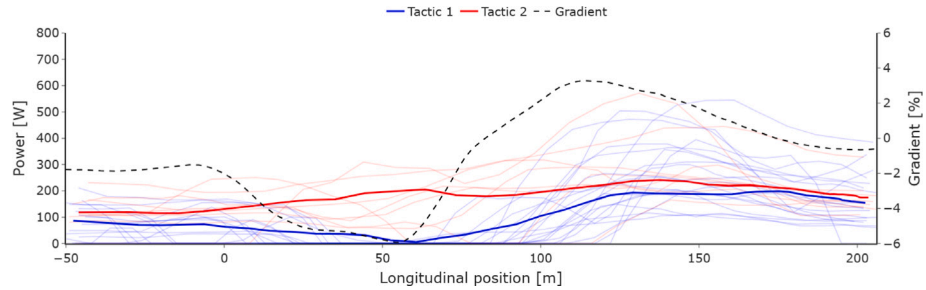

Fig. 5. Tactical behavior on uphills triggered by the transition from prior downhill (Linköping). Note: Position zero indicates the start of the downhill, defined as a gradient steeper than −2 percent. The thick line represents the average power output of individual (thinner) trajectories. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

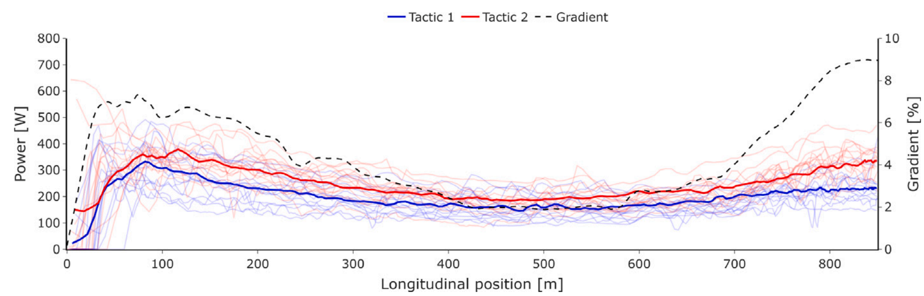

Fig. 6. Tactical behavior on uphills triggered by the length of uphill (Wuppertal). The thick line represents the average power output of individual (thinner) trajectories. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

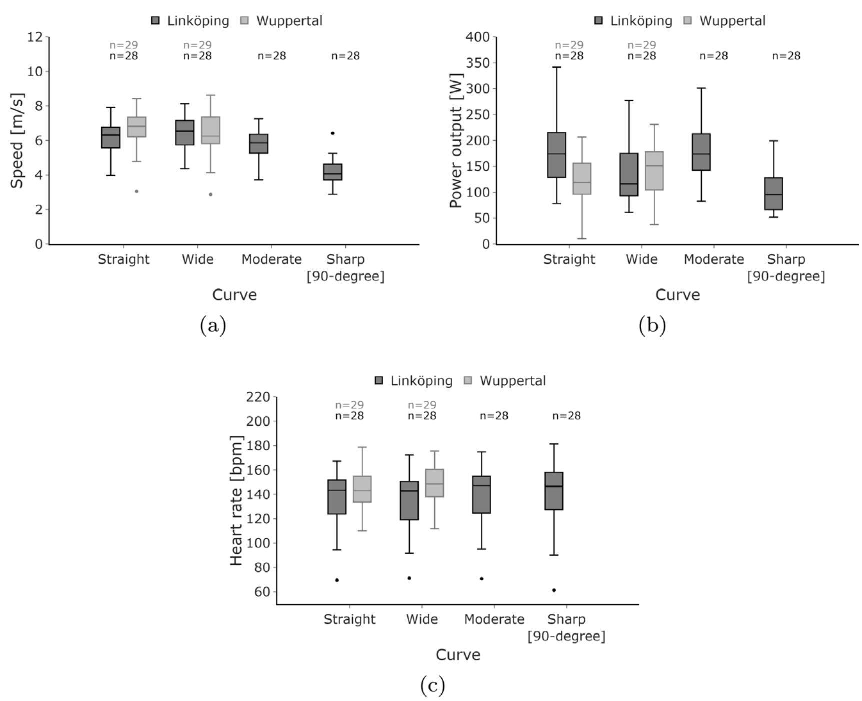

Fig. 7. Impact of horizontal curvature on (a) speed, (b) power output, and (c) heart rate. Note: curves are categorized by their rate of directional change per distance [m^{-1}], with speed, power, and heart rate observations averaged for each curve. The analysis includes observations from flat segments with low wind speeds.

(Linköping) for power output. The Intraclass Correlation Coefficient (ICC) indicates that 32.2% of the total variance in speed (Wuppertal) and 56% (Linköping) may be explained by differences among bicyclists. In contrast, individual differences are attributable to 22.5% (Wuppertal) and 51.4% (Linköping) for power output. The marginal and conditional R^2 values reflect lower proportions, with marginal R^2 capturing the variance explained by fixed effects alone and conditional R^2 including both fixed and random effects. Male participants exhibit higher speeds and power outputs than females across all models. On average, using the combined dataset, males ride 1.074 m/s faster and generate 40.385 W greater power output than females.

Uphill gradients reduce speed (−0.191 to −0.073 m/s per 1% gradient) while increasing power output (+25.016 to +28.876 W per 1% gradient), whereas downhill gradients increase speed (+0.053 to +0.425m/s per 1% gradient) but decrease power output (−21.515 to −13.383 W per 1% gradient). Notably, the coefficients for uphill and downhill

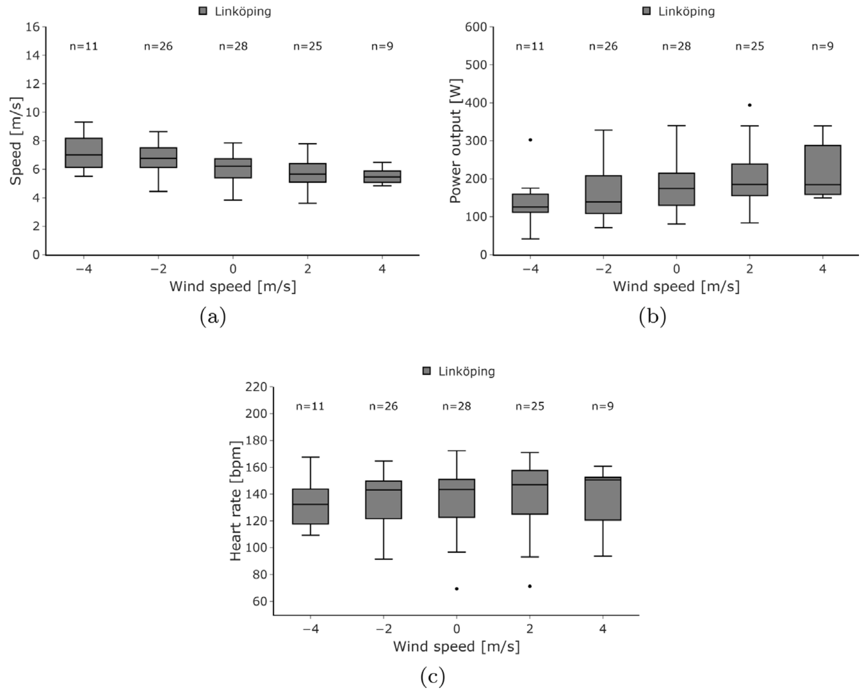

Fig. 8. Impact of wind speed on (a) speed, (b) power output, and (c) heart rate. Note: the analysis includes observations from flat and straight segments.

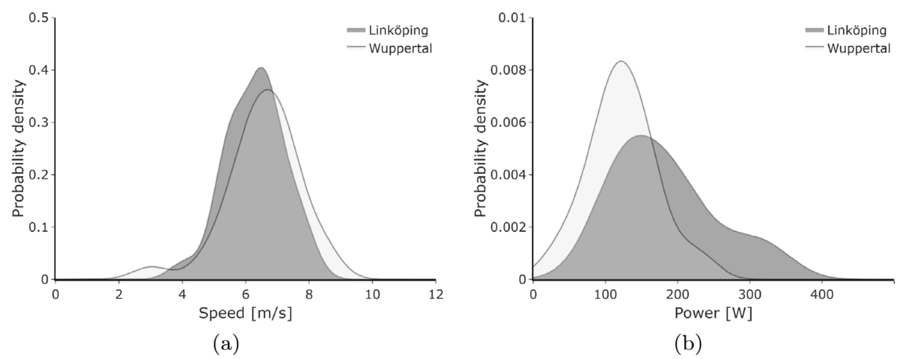

Fig. 9. Distribution of preferred (a) speed and (b) power output. Note: The sample size is 28 and 29 participants for Linköping and Wuppertal, respectively (kernel density estimate).

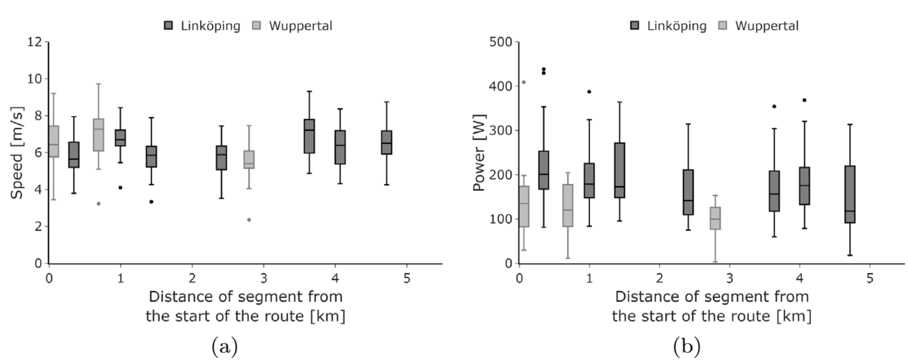

Fig. 10. Distributions of preferred (a) speed and (b) power output over the trip. Note: The sample size is 25 and 20 participants for Linköping and Wuppertal, respectively.

gradients differ significantly in magnitude, indicating their impacts on speed and power output are not equivalent for the same gradient. The random slopes for gradient reveal the variability in how bicyclists respond to these factors (illustrated in Fig. 13). Elevation gain and loss refer to the absolute change in altitude from the start of the uphill or the downhill. Elevation gain decreases speed (−0.18 to −0.038 m/s per 1 m) and has mixed effects on power output, slightly increasing it in Linköping (+0.554 W per 1 m) but reducing it in Wuppertal (−1.197 W per 1 m). The mixed effects on power output may arise from shorter uphills in Linköping, where participants may be more willing to exert additional power, compared to the longer and more demanding uphills in Wuppertal. Elevation loss, on the other hand, increases speed

Table 2
Model results.

	Speed [m/s]			Power output [W]		
	1: Linköping	2: Wuppertal	3: Combined	4: Linköping	5: Wuppertal	6: Combined
Fixed effects: Coefficients (β_0, β_x^1) (Mean over the population)						
Intercept, β_0 [m/s or W]	5.5 [5.021, 5.979]	5.27 [4.79, 5.749]	5.226 [4.779, 5.673]	138.727 [101.26, 176.193]	102.814 [80.979, 124.648]	110.692 [86.148, 135.236]
Gender [m/s or W] {0: Female, 1: Male}	0.759 [0.239, 1.279]	1.074 [0.543, 1.605]	1.075 [0.657, 1.494]	44.277 [3.878, 84.676]	35.128 [10.26, 59.996]	40.385 [17.223, 63.547]
Uphill gradient [m/s or W per 1%]	−0.073 [−0.107, −0.038]	−0.191 [−0.213, −0.169]	−0.177 [−0.236, −0.117]	28.876 [25.099, 32.652]	25.016 [22.289, 27.743]	27.228 [24.874, 29.582]
Downhill gradient [m/s or W per 1%]	0.053 [0.018, 0.088]	0.425 [0.357, 0.492]	0.354 [0.306, 0.403]	−21.515 [−25.152, −17.879]	−13.383 [−15.126, −11.641]	−20.088 [−22.874, −17.303]
Is uphill ahead? [m/s or W] {1:True}	0.214 [0.183, 0.245]	–	0.248 [0.211, 0.285]	3.687 [0.976, 6.399]	–	1.349 [−1.347, 4.046]
Elevation gain [1/s or W/m]	−0.18 [−0.187, −0.173]	−0.038 [−0.04, −0.037]	−0.04 [−0.041, −0.039]	0.554 [−0.045, 1.154]	−1.197 [−1.291, −1.102]	−1.114 [−1.212, −1.016]
Elevation loss [1/s or W/m]	0.311 [0.3, 0.322]	0.044 [0.042, 0.046]	0.042 [0.04, 0.043]	−10.852 [−11.802, −9.902]	−0.236 [−0.344, −0.128]	−0.373 [−0.485, −0.261]
Curvature [m^{-2}/s or Wm/s]	−6.042 [−6.579, −5.505]	–	−6.194 [−6.762, −5.626]	−393.31 [−439.935, −346.685]	–	−221.35 [−262.314, −180.386]
Intersection [m/s or W]	−0.411 [−0.437, −0.384]	−0.231 [−0.279, −0.183]	−0.242 [−0.267, −0.217]	−24.414 [−26.693, −22.136]	−16.96 [−19.597, −14.323]	−21.816 [−23.627, −20.004]
Headwind [– or W s/m]	−0.253 [−0.332, −0.174]	–	−0.211 [−0.224, −0.197]	15.665 [9.876, 21.453]	–	12.005 [11.04, 12.971]
Tailwind [–, W s/m]	0.303 [0.222, 0.385]	–	0.394 [0.379, 0.409]	−12.987 [−17.28, −8.695]	–	−9.801 [−10.876, −8.726]
Location [m/s or W] {0: Linköping, 1: Wuppertal}	–	–	0.034* [−0.407, 0.474]	–	–	18.268* [−8.737, 45.274]
Random effects: intercepts and responses (Std. deviation) (Std. deviation over the population)						
Bicyclist, u_{0j} [m/s or W]	0.749	0.710	0.687	59.343	29.798	53.983
Uphill gradient [m/s or W per 1%]	0.090	0.058	0.229	9.969	7.427	8.940
Downhill gradient [m/s or W per 1%]	0.089	0.183	0.185	9.449	4.486	10.540
Headwind [–or W s/m]	0.205	–	–	14.682	–	–
Tailwind [–or W s/m]	0.211	–	–	10.747	–	–
Model fit						
R^2 Marginal	0.402	0.786	0.678	0.391	0.725	0.58
R^2 Conditional	0.761	0.858	0.827	0.724	0.791	0.782
ICC	0.56	0.322	0.422	0.514	0.225	0.464

1: β_x show changes in one unit speed [m/s] or power output [W] per unit change in predictors, with [ ] indicating 95% confidence intervals.
* p-values > 0.05 (not significant).

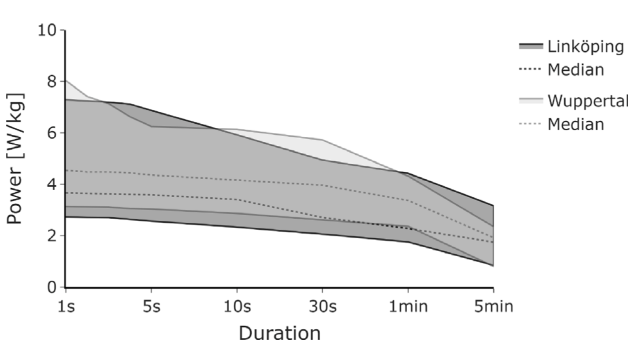

Fig. 11. Maximal power output sustained over time, normalized by total weight.

(+0.044 m/s to +0.311 m/s per 1 m) but decreases power output (−0.236 W to −10.852 W per 1 m), reflecting reduced physical effort during descents. Including elevation gain and elevation loss in the model captures characteristics of hills beyond just the local gradient, such as their length and overall profile. The variable "is uphill ahead" is designed to capture downhill-to-uphill transitions along the route by marking all downhills immediately followed by an uphill, allowing for comparisons with downhills that transition into flat sections. It represents downhills where bicyclists may increase their power output in anticipation of an upcoming uphill. This variable shows a statistically significant increase in power output (+3.687 W) in Linköping, along with a consequent significant increase in speed, reflecting the anticipatory tactic by bicyclists when approaching uphills. Additionally, curvature reduces both speed and power output. Curvature is not included in the Wuppertal models, as the radii are too large to generate a noticeable effect. The presence of intersections lowers both speed and power output.

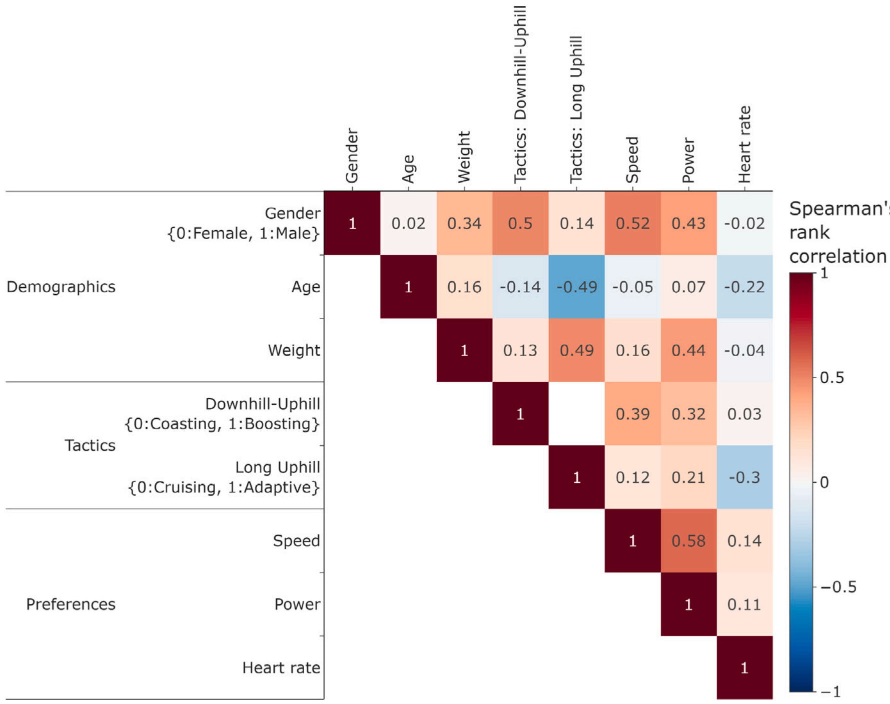

Fig. 12. Spearman's rank correlation (ρ) between individual characteristics, perceptions of effort, tactics, and bicycling preferences.

In Linköping, headwinds reduce speed by −0.253 and increase power output by +15.665 W s/m, while tailwinds increase speed by +0.303 and reduce power output by −12.987 W s/m. The coefficients for headwinds and tailwinds are similar in magnitude, suggesting comparable changes in speed and power output but in opposite directions. Similar to gradients, the responses to wind effects also show significant variation among individuals.

Route familiarity, self-perceptions of commuting style and physical fitness, age, and total weight are tested as predictors in the mixed-effects models, but neither is statistically significant (p-value > 0.05) in explaining the variation observed in speed and power output. Similarly, we include the "location" variable to test whether the unobserved location-specific factors are significant predictors in our data sets. Location is notably not a statistically significant predictor in our models, indicating that any systematic differences between the Linköping and Wuppertal samples that cannot be explained by any of the other variables included in our models, e.g., type of infrastructure (separated bicycle path vs. mixed-traffic), are too small to be observed for these sample sizes. Instead, the observed differences in performance could largely be explained by gender and the characteristics of the trip (gradients, curves, presence of intersections, and wind).

4. Discussion and conclusion

This study presents a methodology using instrumented bicycles to analyze free riding behavior in two different locations. The main objective is to understand how different environmental and infrastructural features influence speed and power output.

The analysis reveals that speeds and power outputs vary substantially between bicyclists and throughout the trip due to infrastructure design and environmental conditions. Speed distributions show reduced variation on steeper uphills and increased variation on steeper downhills. The speed on straight, flat, and windless terrain, referred to as the desired speed, can be seen as a trade-off between travel time and effort minimization, which reasonably corresponds to the observed (desired) power on these segments. The speeds we observe on uphills or against strong headwinds exceed those achievable if bicyclists kept to their desired powers, yet fall short of desired speeds. Hence, we conclude that bicyclists compensate for the greater speed reductions, which would result from maintaining their desired powers, by increasing their power output on inclines and into headwinds. The extent of compensation varies significantly among individuals likely due to differences in physical capacity and preferences or mechanical properties of the bicycles. The observed maximum power output sustained over time also reflects typical power outputs that bicyclists are willing to sustain in utilitarian trips; the observed power curves of participants range from 2 to 8 W/kg over 1 s, significantly lower than those typical in sport bicycling. The mean and standard deviation of desired speeds (when not heavily impacted by infrastructure and environmental factors) are similar in Linköping (6.3 ± 0.9 m/s) and Wuppertal (6.5 ± 1.1 m/s). The higher desired power output observed in Linköping (182.7 ± 70.9 W) compared to Wuppertal (123.5 ± 47 W) may result from seasonal differences in bicycle traffic. Data collection in Linköping during the fall involved heavier clothing, which increases aerodynamic resistance. Within each trip, desired speeds and power outputs vary considerably, with a standard deviation per participant ranging from 0.3 m/s to 1.7 m/s. However, future research needs to identify how much of the variation in these observed desired speeds over a trip stems from actual changes in desired speed versus contextual factors, such as the long-lasting effects of previous infrastructure and anticipatory adjustments for upcoming infrastructure.

We conclude that some bicyclists display tactical behavior, presumably to maintain speed and manage exertion on uphills. By boosting their speed (by pedaling) with the assistance of the downhill, some participants reduce slowdowns and impacts on travel time, which in turn may also reduce the effort needed for the uphill downstream. In contrast, other participants prefer to coast on the downhill. The analysis suggests the "boosting" behavior correlates with male participants and high desired speeds, and that familiarity with the route may be relevant for these patterns to emerge. In Wuppertal, a different behavior emerges when dealing with long uphills. While young participants with relatively high desired power outputs continue to generate more power as the gradient becomes steeper, others maintain a relatively constant power output towards the end of the climb. This indicates that while power output may initially increase with gradient, the length of the uphill ultimately impacts the available power as the climb

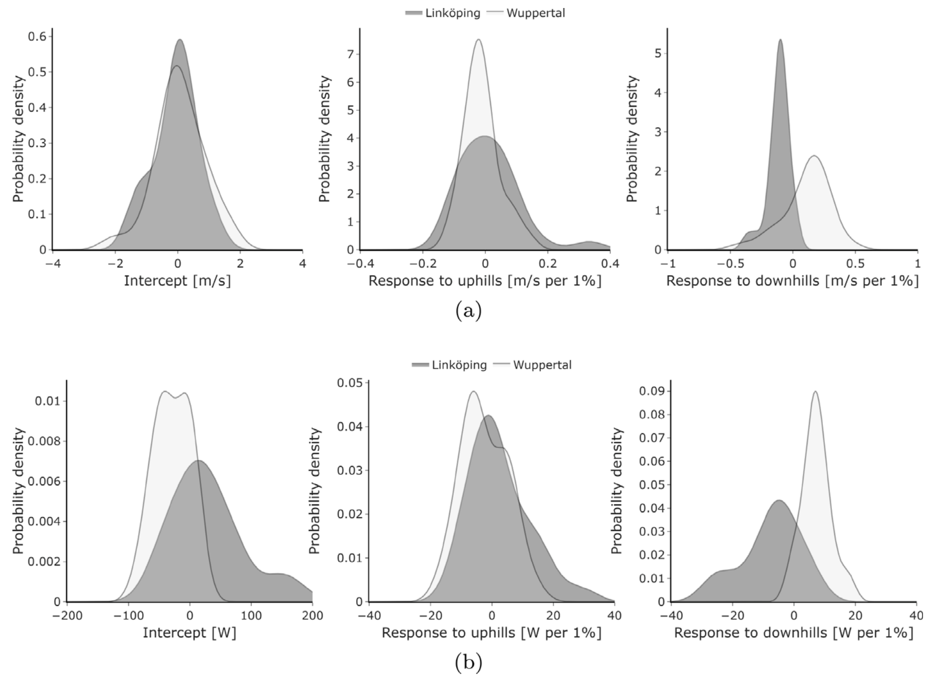

Fig. 13. Distributions of individual intercepts and responses for the combined-locations model of (a) speed [model 3] and (b) power output [model 6] (kernel density estimate). Note: The distributions represent deviations from the average intercept and fixed effect at the population level.

progresses. As physical exhaustion sets in, the power output may no longer correlate with gradient, and instead, it stabilizes or decreases over time on very long hills. Our findings also suggest that steep downhills may be perceived as risky for some participants, indicated by the large variation in speeds—maximum downhill speeds range from 5 m/s to 17 m/s. A limitation in this study is the lack of direct measurements of braking activity, which restricts the analysis of how risk perception influences speed choices on downhills. Future research should explore how much additional speed bicyclists are willing to accept on downhills before braking, i.e., how do trade-offs between travel time and perceived safety affect free riding on downhills.

The mixed-effects models reveal that individual-level variability may account for up to approximately 56% of the total variance in speed and power output in our data sets. Gender is an individual characteristic that shows statistical significance in accounting for variation in speed and power output. In our model estimation, age and total weight are found to be insignificant; gender may already capture the effects of weight differences. Although bicycle type is potentially relevant, it is not included in the models due to limited variation within each location but merits future research. Elevation gain and loss provide additional context about the nature of the terrain, showing how bicyclists adjust their behavior based not only on the local gradient, but also accounting for the physical demands of extended climbs or descents. Moreover, there is a statistically significant variation among individuals in coping mechanisms concerning gradients and wind. Note that the observed power output to compensate for the strongest headwind (4 m/s) is comparable to the power output to overcome a relatively light incline (approximately 2 percent gradient). In this study, we find no significant differences in the magnitude of the impact of wind direction (tailwind vs. headwind) on free speeds, however, further research needs to investigate the effects of higher wind speeds than those observed in this study due to the non-linear relationship between bicycling speed and aerodynamic resistance. Overall, we conclude that the observed differences in speed and power output are largely explained by gender, gradients, curves, presence of intersections, and wind, underlining the importance of these factors in understanding bicyclist behavior.

The relatively small sample size in this study restricts the capability to conduct detailed subgroup analyses, e.g., by bicycle types, commuting styles or physical fitness, or to validate robust models for estimating bicycling behavior across different contexts. In both locations, we study frequent bicycle commuters, with the Wuppertal sample likely including more enthusiastic or research-interested participants due to the lack of financial compensation. Consequently, the observed behavioral variation is likely an underestimate of the true heterogeneity present in bicycle traffic. We expect that a wider variety of bicyclists, including diverse fitness levels, bicycling expertise, and bicycle types, further increases heterogeneity in the impact of infrastructure and wind. Future research should address this by including larger and more diverse datasets with overlapping route features. Nevertheless, our findings demonstrate relevant relationships between hills, curves, and wind and bicyclist behavior, and highlight the substantial heterogeneity in how these factors affect speed (and power output) choices in bicycle traffic. Future research should also expand on free riding on bicycles with electrical assistance and free riding dynamics at various intersections, e.g., approaching, acceleration from a standstill position, etc.

The data collection method implemented in this study allows for observing free riding on a given route. By allowing participants to use a bicycle they are already familiar with, this method enables data collection of naturalistic behavior. This setup facilitates the investigation of how the effects of hills, curves, and wind vary between bicyclists by reducing the effects of measurement equipment and the route traveled. However, there is a limitation in overcoming the learning curve associated with traveling on an unfamiliar route. Selecting a route that can be traveled back and forth, as done in Linköping, or recruiting participants who are familiar with the area where the experiment takes place, as done in Wuppertal, can partially mitigate this issue. Familiarity with the route does not significantly account for the variation in our data, suggesting that the implemented experimental setup does not have a major impact on naturalistic behavior. Modifications to the experimental design could involve having participants travel the route multiple times, or use the equipment to record several commuting trips; however, both modifications require longer data collection times. Having a setup in which participants travel their commuting routes could provide benefits in observing genuine commuting behavior over long periods, but also introduces challenges due to variations in route properties. For example, biases can arise as relaxed commuters might prefer routes with less pronounced gradients, while fast and fit commuters might choose more direct but steeper routes. This variation may inhibit observation under a diverse range of infrastructure conditions for each participant. Road surface quality may further affect bicyclist behavior, as previous research correlates it with comfort and effort, which in turn may impact speed and power choices. Future research should consider surface quality in studies where road surface conditions vary substantially.

Data acquisition and processing using commercially available devices is not overly complex, and may be sufficient for various traffic analyses. Additionally, we find that video recordings and participants' self-record events along the trip are effective for detecting interactions with other road users, providing a comprehensive view of behavior constrained by other road users. Incorporating automated tools for audio and video processing could be beneficial, as manual processing can be time-consuming. Examining constrained behavior can be further explored in future research, with a key focus on deriving distances between bicyclists from either video analysis or additional sensors. Although few participants report minor impacts from instrumentation, such as pedals feeling unusual (due to their thicker design), cameras shifting, or issues with borrowed bicycles (e.g., gearing or seat height), we exclude data from participants who indicate these issues affected their riding behavior to avoid bias, which further reduces the sample size for analysis. Future research should explore ways to minimize these effects.

CRediT authorship contribution statement

Danil Belikhov: Writing – review & editing, Writing – original draft, Visualization, Methodology, Formal analysis, Data curation, Conceptualization. **Guillermo Pérez Castro:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Mathis Titgemeyer:** Writing – review & editing, Methodology, Investigation, Conceptualization. **Fredrik Johansson:** Writing – review & editing, Supervision, Methodology, Funding acquisition, Conceptualization. **Heather Kaths:** Writing – review & editing, Supervision, Project administration, Methodology, Funding acquisition, Conceptualization. **Johan Olstam:** Writing – review & editing, Supervision, Project administration, Methodology, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Co-author is a member of the Editorial Board of the Journal of Cycling and Micromobility Research—Heather Kaths. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Access to the Linköping dataset is available upon request and subject to privacy regulations and ethical approval. The Wuppertal dataset is available at: doi.org/10.5281/zenodo.14391230.

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