TUDelft

Delft University of Technology

Document Version
Final published version

Licence
CC BY

Citation (APA)
Yan, H., Maat, K., & van Wee, B. (2026). Explaining patterns of cycling speed stability and disruption. *Transportation Research Part A: Policy and Practice*, *205*, Article 104855. https://doi.org/10.1016/j.tra.2025.104855

Important note
To cite this publication, please use the final published version (if applicable).
Please check the document version above.

Explaining patterns of cycling speed stability and disruption

Hong Yan [a,*] , Kees Maat [b] , Bert van Wee [a]

[a] Transport & Logistics Group, Faculty of Technology, Policy and Management, Delft University of Technology, Jaffalaan 5, 2628 BX, Delft, The Netherlands
[b] Department of Transport & Planning, Faculty of Civil Engineering and Geosciences, Delft University of Technology, P.O. Box 5048, 2600 GA, Delft, Netherlands

ABSTRACT

Cycling speed is an important attribute of bicycle traffic flow, being related to travel times, safety and road capacity. Although cycling speed changes constantly during a trip, it is typically measured at the trip-average or aggregated level, and microscopic speed fluctuations are rarely studied. This study aims to quantitatively understand the cycling speed stability within a trip and the determinants of speed stability and disruption. To this end, data from bicycle trips tracked with GPS devices are used. A change point detection method, the pruned exact linear time (PELT) algorithm, is adapted to split trip trajectories into segments differing in speed stability. Then, a rule-based algorithm is developed to classify segments into six speed (in)stability patterns: stable, increase, decrease, V-shape (speed decreases followed by increases), reverse V-shape (speed increases followed by decreases) and complicated unstable patterns. Finally, a two-level multinomial model is estimated to examine the determinants of different patterns. The findings suggest that stable patterns account for half the trip distances, and their speed is higher than the speed of unstable patterns. The V-shape pattern is the most frequent unstable type. Intersections, turns and built-up land use are the main causes of unstable speeds. Cycling on physically separate paths tends to involve more unstable speeds than on mixed-use infrastructures, such as bicycle streets and bicycle tracks. This study finds that daily cycling involves a considerable amount of unstable speed. While its effects have not been directly examined, speed instability likely increases travel times and physical effort and is perceived negatively by cyclists. This underscores the potential benefits of a smooth cycling network and highlights the need for future research on the role of speed stability.

1. Introduction

Cities and regions worldwide are increasingly pursuing policies to make cycling more attractive (Buehler & Pucher, 2021), and to this end, planners are working on fast, smooth and safe cycling connections. However, the role of fast and smooth cycling is still hardly reflected in the academic literature. Yet from travel theory, it makes sense to pay attention to this. Transport economists consider travel as a derived demand with travel time as a disutility, so travel time is considered a main driver behind travel choices (Small, 2012). They have also shown that travellers are willing to pay for travel time savings, so it follows from this idea that travel speed is positively valued by travellers and consequently plays a role in travel time theory.

---

* Corresponding author.
E-mail addresses: H.Yan-2@tudelft.nl (H. Yan), C.Maat@tudelft.nl (K. Maat), G.P.vanWee@tudelft.nl (B. van Wee).

In many accessibility and mobility policies, increasing speed is a clear goal, as investments in high-speed trains (Gutiérrez et al., 1996) and bus rapid transit (Lee & Miller, 2018). Apart from increasing vehicle speeds, a smooth traffic flow with stable speeds can also raise speeds by preventing braking and re-acceleration to the desired speed. This can be achieved by removing disruptions and barriers, such as road geometric design optimisation (Gibreel et al., 1999) and traffic signal synchronisation (Adacher et al., 2014). This applies to all modes of transport and increasingly also to bicycles. It is for this reason that new forms of bicycle infrastructure emerge, such as express cycle paths, which allow fast and stable speeds as they are wide, with smooth pavement, and without many intersections (Rayaprolu et al., 2020). In cities, bike streets and green waves for cyclists improve speed stability. Such new forms of infrastructure have been found to attract new cyclists (Skov-Petersen et al., 2017), so it can be assumed that the more stable cycling speeds are, the more competitive and attractive cycling is.

In addition to its influence on travel times (Kircher et al., 2018; Strauss & Miranda-Moreno, 2017), speed stability is assumed to be related to safety and physical effort involved in cycling. First, cycling speed variation during a ride is likely to increase both crash risks and severity (Twisk et al., 2021). Especially, hard braking leads to control loss and crashes over the handlebars, acting as a source of single-bicycle accidents (Frendo, 2010; Schepers & Wolt, 2012). A bigger speed difference between motorised vehicles is related to more frequent passing, speed changes and a higher crash rate (Aarts & van Schagen, 2006; Choudhary et al., 2018). Applying this to cycling, cycling speed changes during interactions between cyclists also tend to cause safety issues, and these changes will occur more frequently due to the increased adoption of electric bicycles, resulting in higher speeds (than city bikes) and larger speed differences (Huertas-Leyva et al., 2018). Second, instability requires extra effort, such as accelerating to the former speed after a stop (Graham, 1998). Probably due to these reasons, cyclists are dissatisfied with routes characterised by unstable cycling speeds (Joo et al., 2015).

Current studies on cycling speeds have mainly examined its determinants related to cyclists, trips and the environment during rides (Yan et al., 2024). It has been found that cyclist and trip characteristics affect the average trip speed, with a higher average speed for men (Romanillos & Gutiérrez, 2020), younger cyclists (Schleinitz et al., 2017), electric bicycles rather than city bicycles (Eriksson et al., 2019) and commuting purposes rather than leisure purposes (Broach et al., 2012). The environment explains cycling speed differences at various locations, with cycling speeds being higher on separate bicycle facilities (Clarry et al., 2019), downhill roads (Flügel et al., 2019), straight roads (Arnesen et al., 2020), roads away from intersections and turns (Strauss & Miranda-Moreno, 2017) and in non-urban areas (Gustafsson & Archer, 2013). However, these results do explain cycling speeds but not cycling speed stability.

To understand the performance of a bicycle network, bicycle traffic researchers, planners and road authorities need knowledge about what cycling speed *(in)stability* is, the extent of (un)stable speed and its determinants. To the best of our knowledge, only one study has examined cycling speed stability (Nabavi Niaki et al., 2018). They observed cyclists' speeds and acceleration at four different road segments, with two segments having consistent bicycle infrastructures (continuous segments) and two segments having changing bicycle infrastructures (discontinuous segments). In one discontinuous segment, the infrastructure changes from a separate path to a shared road, and in another, a separate path shifts from one side of the road to another. The results showed that speed and acceleration have larger variations at discontinuous segments. It illustrates the importance of bicycle infrastructure continuity for speed stability, but four segments can hardly represent the complex bicycle infrastructure network. This highlights a significant knowledge gap in understanding cycling speed stability, with implications for both science and practice.

Speed stability can be regarded as maintaining the free-flow speed. Traffic flow theory states that driver-vehicle combinations move at their free-flow or desired speeds when they are not influenced by other road users. This free speed depends on driver characteristics and vehicle conditions, meaning that it varies across drivers and trips. Free-flow speed is also influenced by road infrastructure, traffic rules, ambient environments and weather conditions, and drivers may adjust their speeds in response to these factors. With the increase in traffic volumes, drivers cannot choose their speed freely and have to adapt their speed to other road users (Hoogendoorn, 2005). To the best of our knowledge, a definition of speed stability, even for cars, is lacking in the literature. Similarly, its determinants are not discussed. In this line, we assume that *(i)* cycling speed (in)stability differs across cyclists and trips, that *(ii)* cyclists maintain a stable speed in an unchanged environment, but that *(iii)* their stable speeds can be disrupted by changes in infrastructure and ambient environment, and by interactions with other road users, including cyclists.

This paper introduces the concept of stability as the extent to which cyclists maintain stable speeds during a ride. Due to disruptions during the ride, cycling speeds are destabilised, and unstable ride segments arise. Therefore, cycling speed stability was analysed in two aspects: (1) the extent to which cyclists can maintain a stable speed and (2) the determinants of speed (in)stability. To this end, cycling data was collected using GPS devices. Tracking points were recorded with their timestamps and locations so the speed at each point could be derived. Segments with various speed (in)stability were detected by applying segmentation using change point detection (CPD), and a rule-based algorithm was developed to classify segments into speed (in)stability patterns. Finally, the determinants of these patterns were modelled on the basis of a multilevel multinomial logistic regression model.

The added value of this paper is threefold. First, it proposes the concept of cycling speed stability, which is an essential factor in travel choices but has hardly been studied. Second, a method combining change point detection and a rule-based algorithm is introduced to recognise speed (in)stability patterns from GPS-tracked trips. Third, this method is used for empirical analysis of speed stability.

The following section explains the dataset and modelling method. The third section describes processes for splitting trips and detecting speed (in)stability patterns, as well as descriptive statistics. The determinants of speed (in)stability and the explanation are reported in the fourth section, while a discussion and conclusion are provided in the final section.

2. Data and variables

2.1. Sniffer bike data

This study used cycling data from the Sniffer Bike project (Snuffelfiets, 2020) from the year 2020. This Dutch project is highly unique worldwide, aiming to increase the understanding of cycling by collecting large-scale data. The province of Utrecht started this project, collaborating with different stakeholders. SODAQ (Dutch company on Internet of Things devices) developed a mobile sensor with various functions, including GPS, weather and emissions monitoring and real-time data uploading; the sensor is affordable, reliable and accepted for long-term measurement. This sensor automatically processes measurements around every 13 seconds when bicycles are moving and stops after a few minutes of standstill. Participants were asked to fix the sensor kit on the handlebars of their private bicycles. Their cycling data are managed and visualised by Civity (a Dutch company) and validated by the Netherlands National Institute for Public Health and the Environment (RIVM). The project is anonymous, without collecting participant and bicycle characteristics. Participants were recruited from municipalities, resident groups and regional communities. Although they may not fully represent Dutch cyclists, we do not expect a strong influence of self-selection on speed stability. The study was based in the province of Utrecht and its surrounding cities. Cycling was unevenly distributed within this area (Fig. 1).

In 2020, the sample consisted of 507 cyclists, who reported 60,225 trips, based on 7,349,069 tracking points. After data filtering (see Section 3.1) and deleting missing data (see Section 2.3), there are 5,672,552 tracking points from 59,928 trips of 505 cyclists.

2.2. Speed (in)stability patterns

To understand cycling speed (in)stability, (in)stability patterns along trips were detected, which are also the dependent variable of the final model. First, a change point detection method, in particular the PELT algorithm (Truong et al., 2020), was adopted to divide trips into segments differing in the extent of speed stability. Then, a rule-based algorithm was developed to classify these segments into the stable pattern, and the five unstable patterns: increase, decrease, V-shape, reversed V-shape, and complicated unstable patterns. The detailed process is described in Section 3.

2.3. Determinants of cycling speed (in)stability

As discussed in Introduction, we assume that cycling speed (in)stability is influenced by (1) cyclist and bicycle characteristics, (2) bicycle infrastructure, (3) ambient environment and (4) other road users. The Sniffer Bike dataset does not include cyclist and bicycle characteristics. However, including the average trip speed may help control for self-selection regarding the cyclist and the bicycle. Moreover, it can examine whether higher or lower cycling speeds are associated with speed (in)stability. The average trip speed was calculated using the trip distance and time. Variables for other aspects were also developed. Meanwhile, these variables show a hierarchical structure of trip and point levels (Table 1).

Bicycle infrastructure attributes are from a digital road network map collected by the Fietsersbond (Dutch Cyclists' Union), including bike lane types, intersections, bridges and tunnels. Each tracking point was assigned these attributes from its nearest segment (if accessible by bicycle), while the point was labelled as missing data if no bicycle accessible segment was found within 50 metres of it. Except for "before/after turns/intersections", other attributes were derived directly from the Fietsersbond data. A turn was recognised if two road segments formed an angle over 80°, and right and left turns were distinguished. Points within 30 m before or after a right/left turn were labelled as "before/after right/left turns". Similarly, points within 30 m of intersections were recognised as "before/after unsignalised/signalised intersections". There are six bike lane types. The bike path along the road is physically separated from main
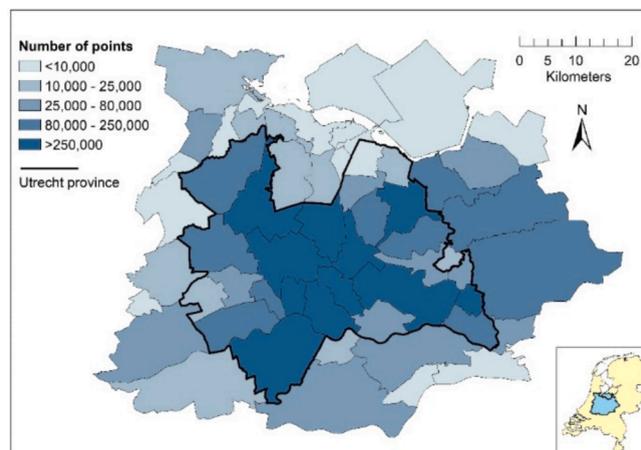

Fig. 1. The study area and the distribution of tracking points.

Table 1
Variable descriptions.

Variable		%/Ave.	Mean speed (km/h)	% of stable pattern
Trip level				
Day of a year	Weekday (ref.)	76.1	19.1	49.9
	Weekend	20.7	18.3	53.1
	Holiday	3.2	18.1	55.2
Peak hour	Non-peak hour (ref.)	66.2	18.5	51.4
	Morning peak hour	13.0	20.5	49.4
	Evening peak hour	20.8	19.2	49.6
Light condition	Sunlight (ref.)	67.0	18.8	50.7
	Twilight	29.5	19.3	50.9
	Darkness	3.5	18.2	50.7
Average trip speed	(km/h)	17.9		
Tracking point level				
Bicycle lane types	Pedestrian areas	0.4	15.7	30.2
	Residential roads (ref.)	39.5	18.9	53.4
	Bike street	11.9	20.0	58.9
	Bike track (separated with lines from road)	2.3	18.9	53.4
	Bike path (physically separated from road)	31.3	18.8	45.2
	Solitary bike path	14.7	18.3	48.9
Intersection	Non-intersection (ref.)	96.6	19.1	51.8
	Roundabout	0.7	16.6	31.7
	Unsignalised	1.0	15.6	29.8
	Signalised	1.7	9.4	9.8
Before/after intersection	Others (ref.)	96.2	19.0	51.7
	Before signalised	1.0	16.9	21.0
	Before unsignalised	0.9	18.7	35.9
	After signalised	1.0	16.2	17.5
	After unsignalised	0.9	17.1	33.2
Before/after turns	Others (ref.)	90.1	19.3	53.9
	Before right turn	3.3	15.9	24.0
	Before left turn	3.7	15.1	21.1
	After right turn	1.4	15.0	22.9
	After left turn	1.5	14.6	21.0
Bridge and tunnel	Non-bridge/tunnel (ref.)	97.4	19.0	51.2
	Bridge	1.6	16.7	26.6
	Tunnel	1.0	18.9	35.0
Slope	Flat roads (ref.)	98.1	19.0	51.4
	Uphill	1.1	14.2	20.7
	Downhill	0.8	16.5	18.9
Land-use	Built-up area (ref.)	34.3	17.7	42.5
	Semi built-up area	2.0	18.5	45.2
	Industry/Transport area	14.5	18.2	40.4
	Green area	49.2	20.0	59.8

roads, while bike tracks use road markings or different surfaces to separate from main roads. Solitary bike paths are located away from motorised vehicle roads. Bike streets allow cars, but bicycles have priority. Residential roads have no bike infrastructure, and in pedestrian areas cyclists are usually not allowed to cycle (although they sometimes do).

The slope is also regarded as an infrastructure attribute, derived from the raster altitude map (AHN, 2020). Tracking points have the altitude of the pixel in which they are located. The slope of one tracking point was calculated based on its horizontal distance to its preceding point and the altitude difference between these two points. Slopes were then categorised into uphill ($slope > 2°$), flat road ($-2° \leq slope \leq 2°$) and downhill ($slope \leq -2°$).

Ambient environments include land use and sunlight conditions. Land use was derived from a digital geometry of land use (CBS, 2015), classified into 13 types, and further grouped into four types in this study: built-up, semi built-up, industry/transport (industrial areas, greenhouse, main road, railroad and airport) and green areas (agriculture, forest, dry natural terrain, wet natural terrain, recreation and water). The dominant land-use type within the 50-metre radius circular buffer of a tracking point was considered its land-use type.

The sunlight condition is a trip-level variable, constant within a trip, determined by the midpoint of the trip. It changes with the time of the year and locations. However, our study area is relatively small, in which the sunlight only has a tiny difference across places, and therefore we only considered the changes with time of a year. Three types of sunlight conditions were considered from bright to dark: sunlight, twilight and darkness. The sunlight is the period from sunrise to sunset, with direct solar illumination. The twilight refers to the condition that the sun is 0° to 18° beneath the horizon, when the sun illuminates the lower atmosphere, and there is still natural light. The darkness occurs when the sun reaches 18° below the horizon, and the natural brightness is nearly zero. The periods of these three light conditions were based on the location of Utrecht city, which is the centre of the study area and has the biggest percentage of tracking points.

Data on other road users was unavailable, while temporal factors, including days of the year and peak-hour trips, can partly

represent traffic density. Similar to the sunlight condition, these variables were calculated based on the midpoint of each trip. Days were categorised into national holidays, weekends and weekdays. Peak-hour trips have three types: morning peak hours from 6:30 to 9:00 on weekdays, evening peak hours from 16:00 to 18:30 on weekdays and non-peak hours at other times. Traffic is denser during weekdays and peak hours. In addition, trips during these periods tend to be commuting trips, influencing the overall trip (in)stability.

All considered determinants of cycling speed stability are summarised in Table 1, distinguishing the trip and point levels. For categorical variables, the average speed and the percentage of stable patterns are also reported.

2.4. Two-level multinomial logistic model

This analysis estimated a multilevel multinomial logistic regression to investigate the bicycle infrastructure, ambient environment and temporal situations on which cyclists tend to have various unstable speed patterns rather than the stable pattern. It was performed by developing a generalised structural equation model, using the GSEM command of Stata 17. Tracking points were chosen as the study unit. Cycling speed stability patterns were detected based on segments, so it would therefore be logical to consider segments as units in the explanatory model. However, segments are homogeneous with respect to the stability pattern, but can be heterogeneous with respect to environment and infrastructure characteristics. Those characteristics should thus be aggregated from tracking point characteristics to segment characteristics, but this is not possible for qualitative characteristics. It is therefore appropriate to estimate the model with tracking points as units.

The random intercept effect of trips (multilevel model) was considered because of the nested data structure: trips and tracking points. A trip consists of many tracking points, which share trip attributes and are not fully independent. The random effect can represent unobserved trip characteristics, reducing the potential influence of missing variables at the trip level on the outcome of point-level variables. In the Sniffer Bike dataset, a cyclist made several trips, meaning that trips are not independent but nested into cyclists. We tried to estimate a three-level model (cyclists, trips and points), but it did not converge probably due to the small difference between cyclists. Consequently, we estimated a two-level (trips and points) multinomial logistic model.

Suppose that the dataset has N tracking points at level 1 (the point level) nested within J trips at level 2 (the trip level), with n_j points in trip j. The nominal response y has C categories, and the response probability of point i in trip j for category k is defined as $\Pr\left(y_{ij} = k\right) = \pi_{kij}$. Among C categories, one category is chosen as the reference, and then the log-odds of being in one of the remaining categories rather than the reference category are modelled. Suppose we have P point level explanatory variables $xpoint_p$ and Q trip level explanatory variables $xtrip_q$, the model for the contrast between response category k and the reference category 1 for point i in trip j can be written as

$$\log\left(\frac{\pi_{kij}}{\pi_{1ij}}\right) = \beta_{0k} + \sum_{p=1}^{P} \beta point_{kpij} xpoint_{pij} + \sum_{q=1}^{Q} \beta trip_{kqj} xtrip_{qj} + \mu_{kj} \tag{1}$$

where $k = 2, \cdots, C$,

$$\mu_{kj} \ N\left(0, \sigma_u^2\right)$$

β_{0k} is the intercept in the equation contrasting the kth and 1st response categories, and it is interpreted as the log-odds that a point with $xpoint_{pij} = 0$, $xtrip_{qj} = 0$ and $\mu_{kj} = 0$ will be in category k rather than category 1 of the response y.

The parameter $\beta point_{kpij}$ is the effect of a one unit change in $xpoint_{pij}$ on the log-odds of response category k versus response category 1 after adjusting for trip-level variables and random effects. This can also be seen as a cluster-specific effect, namely the effect of point-level variables among points in the same trip.

$\beta trip_{kqj}$ represents the contextual effect, the trip-level variable $xtrip_{qj}$ on trip j points' log-odds that is over the effect of their point-level variables.

The random intercept effects μ_{kj} allow the log-odds to vary across trips. If $\mu_{kj} > 0$, it is expected that the ratio of π_{kij} to π_{1ij} to be higher than the average for points in trip j. Similarly, a negative μ_{kj} indicates that points in this trip have a below-average chance of being in category k rather than category 1.

3. Speed (in)stability

This section first describes methods for detecting speed (in)stability patterns, followed by the description of these patterns.

3.1. Speed (in)stability detection

The purpose of speed (in)stability detection is to split a trip into segments with different degrees of (in)stability and to categorise these segments into several (un)stable patterns. Segmentation is necessary because cycling speed stability varies during a ride and is typically interrupted by all kinds of events and changes in the infrastructure and the environment. Four steps are identified.

Speed calculation. The speed of a tracking point was calculated by dividing the Euclidean distance to its preceding point by the time difference between these two points. The distance and time difference were derived from the timestamps and locations (longitude and latitude) recorded by the sensors.

Data filtering discarded tracking points in stationary phases and trips being high-speed outliers. Stationary phases are short stops within a trip, such as shopping and picking up children, unrelated to cycling speed stability. It is common practice to detect these phases with a rule-based algorithm, using the fact that they are characterised by a low speed and a relatively long duration (Li et al., 2019; Wolf, 2000). In this study, we used the same criteria as Wolf (2000): if ten or more consecutive tracking points (lasting more than 120 s) have a speed lower than 5 km/h, they were recognised as unmoving points and filtered out. Typically, a speed of 5 km/h is regarded as the walking speed (Meijaard et al., 2007), at which cyclists can hardly keep balance. High speeds may indicate bicycles being transported by trains or cars. Trips with an average speed over 45 km/h, corresponding to the legal maximum speed of speed pedelecs, were removed. Data filtering removed around 11 % of tracking points.

Segmentation was achieved with change point detection (CPD), which can find changes in attributes of time series data that represent transitions between states. It has been applied in various areas, including finance, bio-informatics and climatology (Aminikhanghahi & Cook, 2017; Truong et al., 2020) and recently also in the field of transport (Bian et al., 2021). The study closest to our study is Zarindast et al. (2022), who used CPD for GPS-based speed data to identify traffic congestion.

In our study, cycling speed is time series data, and the speed attributes vary across segments with different states of speed stability, so CPD can be used to detect changes in speed states. Although there are constantly small fluctuations in speed during cycling, CPD aims to identify the transition to another state of speed, where slight fluctuations are again possible.

For a given ordered sequence of data, $y_{1:n} = (y_1, \cdots, y_n)$, assuming it has m change points at positions $\tau_{1:m} = (\tau_1, \cdots, \tau_m)$, $\tau_0 = 0$ and $\tau_{m+1} = n$, m change points divide data into $m+1$ segments, with the ith segment including data points $y_{(\tau_{i-1}+1):\tau_i}$. Commonly, change points are detected by minimising the algorithm:

$$\sum_{i=1}^{m+1} \left[C\left(y_{(\tau_{i-1}+1):\tau_i}\right) + \beta \right] \tag{2}$$

where C is a cost function of homogeneity of the ith segment, with C being low if this segment is homogeneous. β is the penalty to avoid overfitting, with an increased penalty reducing the complexity and frequency of detected change points. Change point detection recursively divides the data into segments and calculates the goodness until the most optimal set of change points is obtained.

This study used the pruned exact linear time (PELT) algorithm, which prunes all τ that cannot minimise algorithm (2) at each iteration to reduce calculation time (Killick et al., 2012). It has been proven to be faster and more accurate than other change point detection algorithms (Dorcas Wambui, 2015). Change point detection was performed using the Ruptures Python library (Truong et al., 2020). After test and comparison, we set a medium overfitting-penalty (β), which ensures recognition of major speed changes and avoids considering small speed fluctuations.

We performed CPD in three steps: (1) the raw speed data was used to recognise change points, (2) the raw speed data was pre-processed, and (3) change points were detected with pre-processed speed data. The steps are detailed below:

Step (1): change point detection was performed with raw speed data. The result shows that change points between stable and
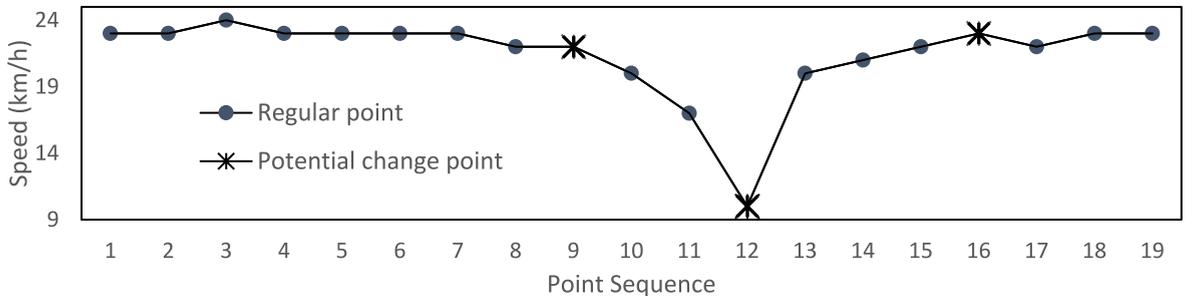
a. raw speed data
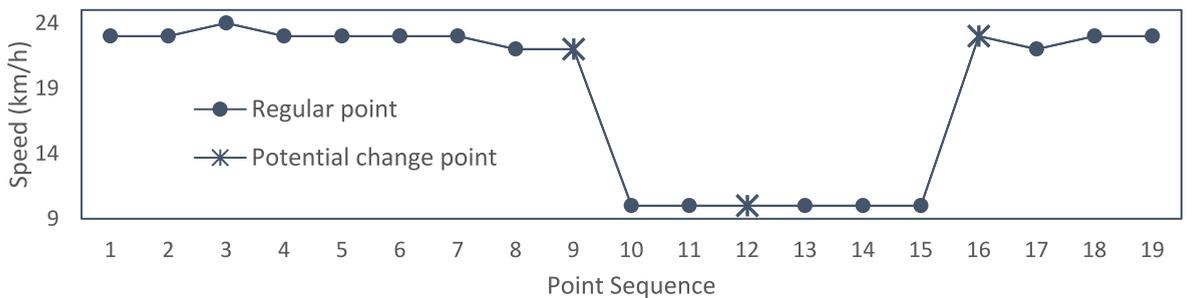
b. potential changing speeds at increasing and decreasing phases

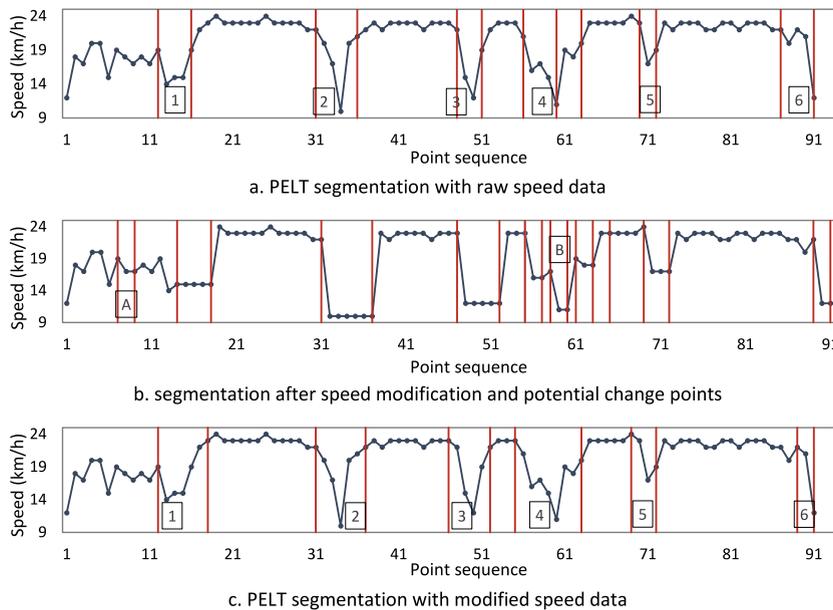**Fig. 2.** An example of raw speed data pre-process.

unstable segments are not well detected (described in Step 3). This is caused by some mismatches between the characteristics of CPD and cycling speed data. CPD identifies change points to ensure the homogeneity of a segment and heterogeneity between neighbouring segments. However, in many cases, cyclists accelerate or decelerate not abruptly but gradually, so the speed change can be small at the change points between stable and unstable parts (see a in Fig. 2). In addition, cycling speeds during unstable segments can vary significantly.

Step (2): raw speed data was pre-processed to allow the homogeneity of speed in speed increase or decrease segments. This process assigns the speed of the tracking points in a continuously ascending or descending phase the value of the point that deviates the most from the mean travel speed within this phase (see Fig. 2). Stable speeds are usually close to the average trip speed, and choosing the most deviated speed can ensure a clear speed difference between possible unstable and stable segments. The start and end tracking points of these continuously ascending or descending phases are defined as potential change points. However, these potential change points are only related to speed increase and decrease, but ignore other complicated segments. In addition, it captures all fluctuations in speeds, which are not the aim of segmentation. So, the PELT method is needed to reach the global minimum of equation (2). The speed pre-process aims only for better detection of change points, and after segmentation, the raw speed was used for segment classification and the speed stability analysis.

Step (3): CPD (the PELT algorithm) was executed with pre-processed data, which works better than with raw data (Fig. 3). Fig. 3a is the result of PELT with the raw speed data, 3b shows modified speeds with boundaries of continuously ascending or descending phases as potential change points, and 3c is the PELT result with the pre-processed data, while for ease of interpretation, the raw speed data was shown. The vertical lines are the positions of detected change points, and points on the lines belong to the preceding segments of the lines. Compared with the results from the raw data (a and c in Fig. 3), the PELT algorithm with pre-processed data recognises complete speed increase and decrease phases (positions 1, 2 and 3). In addition, it successfully detects one more decreasing phase (position 6) and two more phases with speed decrease followed by increase (positions 4 and 5) in this example. Potential change points found by speed pre-process (b in Fig. 3), however, result in many short segments (positions A and B). This result illustrates that it does not consider the speed differences between neighbouring segments, failing to get the global optimum. These examples show that the pre-processing of speed data improves the performance of the PELT algorithm for our purpose.

Classification categorised segments retrieved from the PELT algorithm into different speed (in)stability patterns. First, by observing speed changes of segments in speed-time graphs (e.g. c in Fig. 3), we recognised (a) the stable pattern, and the unstable patterns, including (b) increase, (c) decrease, (d) V-shape, (e) reversed V-shape, and (f) complicated unstable patterns (Fig. 4). Then, a rule-based algorithm was developed to classify all segments into these six patterns. For increase, decrease, V-shape and reversed-V patterns, this classification algorithm primarily relies on the shape of each segment's speed-time graph, supplemented by specific speed criteria. Increase and decrease patterns were first recognised, followed by V-shape and reversed V-shape patterns, and finally the stable and complicated unstable patterns were separated with a speed threshold.

The speed change within a segment was used to distinguish stable and complicated unstable patterns. Stable segments show limited variation in speed, i.e. they have a small speed range. However, existing studies have hardly focused on stable speeds and therefore no definitions for this speed range are available. We conducted a local sensitivity analysis for speed ranges varying from 4 km/h to 8 km/h. A speed range below 4 km/h is considered entirely acceptable during daily cycling, while a speed difference exceeding 8 km/h is

a. PELT segmentation with raw speed data

b. segmentation after speed modification and potential change points

c. PELT segmentation with modified speed data

* Vertical lines are positions of change points, and points on lines belong to their preceding segment

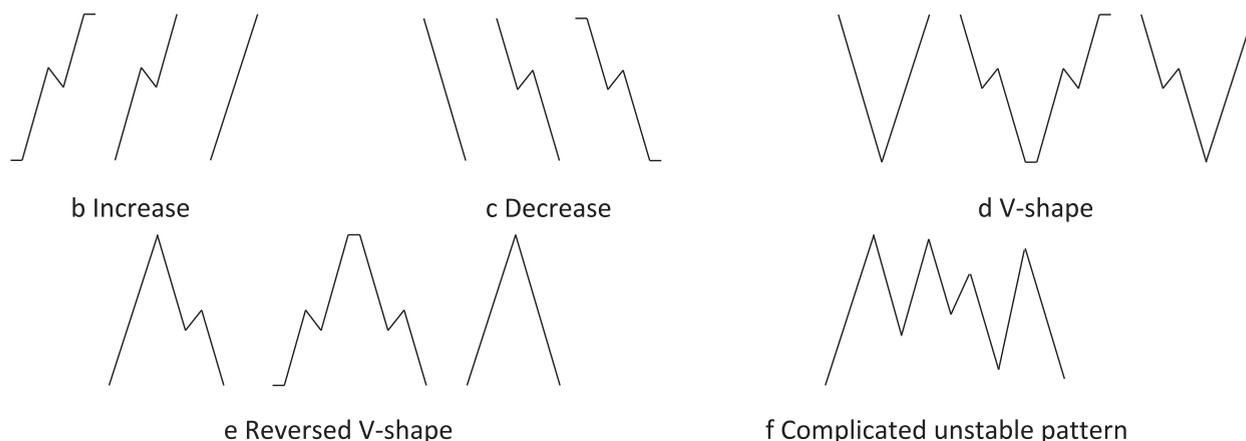**Fig. 3.** Steps in change point detection.

Fig. 4. The illustration of five unstable patterns.

apparently too high given an average speed of 19 km/h. With the speed range increasing from 4 to 8, the distance covered by stable patterns, which will be introduced in Section 3.2, shows a small increase. In addition, the final modelling results hardly change in the direction and significance levels of coefficients, with only small changes in their magnitudes. Therefore, we consider the results as robust. The upper limit of the speed range for the stable pattern was set as 5 km/h.

A speed threshold is also applied for identifying increase and decrease patterns, aiming to exclude segments showing an increase or decrease trend but with minimal speed change. We tested thresholds ranging from 3 to 5 km/h and found robust model results. Finally, we chose 3 km/h to retain as many observations as possible.

After classification, there is an uncommon case where an increase segment and a decrease segment are interconnected. This is caused by separating a V-shape or reverse V-shape segment into two segments during change point detection. Since we are interested in complete speed changes, two connected increase and decrease phases were merged into V-shape or reverse V-shape patterns.

Very short segments with fewer than five points were excluded from the complicated unstable and stable patterns, as stable and complicated unstable cycling should last relatively longer. These short segments were defined as a single pattern if they have only one point and as short segments otherwise.

3.2. Description of stability patterns

Segments with a stable pattern are clearly different from those with unstable patterns in share, average speed and speed standard deviation (Table 2). Stable segments account for half of the total distance, while among unstable segments, the complicated unstable segment has the highest distance share. V-shape segments account for 26 % of all segments and cover around 16 % of the distance. In addition, more than 20 % of V-shape segments decelerate below 5 km/h, which is walking speed and can be regarded as a stop, and another 30 % decelerate below 12 km/h, at which cycling cannot maintain motion stability itself (Meijaard et al., 2007; Schwab et al., 2012; Twisk et al., 2017). The distance share of increase and decrease is small. Stable segments have a lower speed standard deviation than all unstable segments. Their average speeds are higher than those of unstable segments, except for reversed V-shape segments.

Table 2
Descriptive analysis of speed patterns of segments.

Segment patterns	Number	Share (%)	Mean speed (km/h)	Standard deviation of speed	Distance (%)	Duration (%)
Stable	261,420	28.7	19.4	1.0	49.5	47.0
Complicated unstable	96,307	10.6	19.2	3.1	17.2	16.3
Increase	59,853	6.6	16.9	3.1	2.8	3.2
Decrease	57,372	6.3	17.4	2.9	2.7	2.9
V-shape	234,274	25.7	16.2	3.8	15.9	18.3
Speed decreases to below 5 km/h	52,227		11.1	6.8	2.9	4.7
Speed decreases to 5 – 12 km/h	71,105		14.7	3.6	4.3	5.3
Speed decreases to over 12 km/h	110,942		19.5	2.4	8.7	8.3
Reversed V-shape	90,344	9.9	19.6	2.6	7.6	7.3
Short segments	107,117	11.8	16.5	0.8	4.1	5.0
Single	4044	0.4	14.6	0.0	0.0	0.0
All	910,731	100	17.9	2.3	100	100

4. Model results and explanation

The model explains the likelihood that tracking points fall into one of the unstable patterns, with the stable pattern as the reference category (Table 3). Each column shows the results for a contrast between a response unstable pattern and the reference stable pattern. The coefficient represents the effect of a one unit increase in independent variables on the odds of being in an unstable pattern rather than in a stable pattern, holding all other predictors constant. For example, the odds of being in the complicated unstable pattern rather than the stable pattern are expected to decrease by 13.0 % (1–0.870) for trips during weekends compared to weekdays, and by 16.1 % (1–0.839) for holidays. This section describes the model results for each factor group, followed by an explanation of the results.

4.1. The temporal factors and average trip speed

The temporal factors have a relatively minor influence on speed stability. Trips during weekends and holidays are less likely than trips during weekdays to have unstable patterns rather than the stable pattern, especially the complicated unstable pattern. Similarly, trips during morning peak hours have fewer unstable patterns compared to non-peak hours. By contrast, evening peak hours are hardly different from non-peak hours in cycling speed stability, with slightly more increase patterns.

The temporal factors are related to trip purposes and traffic volumes, which influence interactions between cyclists, therefore affecting speed stability. Bicycle traffic with mixed trip purposes has a large speed difference among cyclists, causing more interactions between them, so cyclists tend to have unstable cycling speeds. Similarly, higher cycling volumes force cyclists to adjust their speeds to

Table 3

Estimates from the two-level multinomial logistic model of cycling speed patterns (reference: stable speed pattern)1.

Variables	Complicated unstable	V	Reversed V	Increase	Decrease
Day of a year, weekday as ref.					
Weekend	0.870	(0.996)	0.951	0.949	0.943
Holiday	0.839	(1.036)	0.915	0.921	0.942
Peak hour, non-peak hour as ref.					
Morning peak hours	0.871	0.897	(1.007)	0.904	0.936
Evening peak hours	(1.010)	(0.991)	(0.981)	0.972	(0.997)
Sunlight conditions, with sunlight as ref.					
Twilight	0.912	0.973	0.972	0.950	0.968
Darkness	0.824	0.885	(1.038)	(0.982)	(1.048)
Average trip speed	1.125	1.053	0.992	1.040	1.039
Bike lane types, residential road as ref.					
Pedestrian areas	1.675	1.876	1.728	1.980	2.586
Bike street	0.718	0.813	0.890	0.776	0.726
Bike track (separated with lines from road)	0.930	0.854	1.091	0.890	0.888
Bike path (physically separated from road)	0.982	1.177	1.149	1.055	0.981
Solitary bike path	1.335	1.179	1.294	1.251	1.131
Intersection type, non-intersection as ref.					
Roundabout	1.634	2.532	1.412	1.474	2.143
Unsignalised intersection	1.573	2.872	1.358	1.660	1.988
Signalised intersection	3.117	12.820	2.275	5.048	4.276
Before/after intersection, normal road as ref.					
After unsignalised intersection	1.540	2.467	1.309	1.902	1.451
Before unsignalised intersection	1.395	2.063	1.267	1.186	1.590
After signalised intersection	2.401	7.316	2.073	4.735	1.839
Before signalised intersection	1.954	5.135	1.573	2.250	2.746
Before/after turn, straight road as ref.					
After right turn	3.232	4.437	2.421	4.572	3.158
Before right turn	3.016	3.939	2.282	2.527	4.826
After left turn	3.411	5.013	2.537	5.038	3.251
Before left turn	3.228	4.669	2.570	2.815	5.344
Bridge/tunnel, normal road as ref.					
Tunnel	1.559	1.042	1.853	1.654	1.598
Bridge	2.226	2.190	2.939	2.467	2.032
Slope, flat road as ref.					
Downhill	2.560	2.992	4.683	3.600	2.992
Uphill	2.716	3.743	3.307	3.333	3.508
Land-use, built-up area as ref.					
Semi built-up area	0.845	0.834	1.055	0.811	0.813
Industry/transport use area	0.836	0.920	1.079	0.805	0.808
Green area	0.519	0.532	0.739	0.468	0.453
Constant	0.033	0.155	0.185	0.042	0.039
Trip Variance	49.107				
Log likelihood	− 6902095.2				
Number of trips	59,928				
Number of observations	5,672,552				

Parameters are significant at $p < 0.01$. Insignificant parameters are in brackets.

others. During weekends and holidays, roads are less busy, so cyclists are less influenced by others, resulting in stable cycling speeds. During morning peak hours, despite high traffic volumes, most cyclists have a commuting purpose, tending to keep a high pace and avoid stops, so they have relatively stable speeds. In contrast, evening peak hours slightly differ from non-peak hours in cycling traffic density and trip purposes, leading to the similarity in cycling speed stability.

Faster trips are related to more unstable patterns, with the exception of the reversed-V pattern. For each km/h increase in the average trip speed, the odds of being in an unstable pattern rather than the stable pattern increase by around 4.0 % (for increase, decrease and V-shape patterns) and 12.5 % (for complicated unstable patterns). One possible explanation is that faster cyclists tend to have more interactions with other cyclists and are more likely to adjust their speed during intersections and turns.

4.2. Bicycle lane types

Speed stability differs across bike lane types. Pedestrian areas cause unstable cycling speeds (the odds ratio of becoming in any unstable type is around 2 compared to the stable type). Bike streets, in contrast, have the lowest odds ratios for all instability patterns (0.72–0.89) among all bike lane types. Similarly, bike tracks (separated with lines from the main road) are less likely than residential roads to have unstable speed patterns, meaning that cycling is relatively smooth here. Only the reversed-V pattern is relatively frequent. Cycling on bike paths, physically separated from roads, tends to show unstable patterns. This is even more the case for solitary paths.

The differences in width and the bicycle volume, which are highly related to the frequency of interaction between cyclists, are assumed to contribute to variations in speed stability across these bike lane types. Overtaking is a primary interaction involving four simple unstable patterns. Three overtaking strategies have been recognised in car traffic and in drivers overtaking bicycles, including flying, accelerative and the piggybacking strategies (Farah et al., 2019). It is reasonable to expect that cyclists have similar overtaking strategies, as observed by Mohammed et al. (2019). In the flying strategy, cyclists maintain their speeds when overtaking others. By contrast, the accelerative strategy is that cyclists slow down and may follow others for a while before accelerating to overtake. Decrease, increase and V-shape patterns occur in this strategy. The piggybacking strategy means that two or more cyclists in a row overtake others, and these cyclists take flying or accelerative strategies. In addition, the fourth strategy is widely observed in daily cycling; cyclists accelerate to overtake others and decelerate to their free-flow speeds after overtaking, causing reversed V-shape patterns. This happens when cyclists cannot cycle parallel to each other for a long time.

On bike streets, cyclists share the road with motorised vehicles, and cyclists have priority while cars are restricted to a low speed, so the shared space does not pose major safety risks for cyclists. In addition, bike streets are the widest bike infrastructure, with the width of a wide bike street being at least 4.5 m (CROW-Fietsberaad, 2015) and have a relatively low bicycle volume (Uijtdewilligen et al., 2022), providing cyclists with enough space and resulting in few interactions between them. Even in the case of overtaking, cyclists can take the flying strategy without heavy speed changes, resulting in smooth cycling.

Bike tracks are separate from the main road by road markings. Although they are narrow, bicycle volume is relatively low (Uijtdewilligen et al., 2022), and cyclists can use the car lanes to overtake other cyclists, avoiding large speed changes. However, in cases when cyclists cannot use car lanes for a long time, due to car traffic, they may take the fourth strategy, causing more reversed-V shape patterns. Bike tracks are also less attractive to recreational cyclists, which reduces speed differences and interactions between cyclists.

Bike paths physically separated from roads, however, are busy (Uijtdewilligen et al., 2022), increasing interactions between cyclists and reducing speed stability. In addition, the relatively constrained space, with a recommended minimum width of two metres for a bidirectional bike path within built-up areas (CROW, 2022; Schepers et al., 2023), prevents cyclists from using the flying strategy for overtaking, causing more unstable patterns. Especially, the frequent accelerative strategy results in more V-shape patterns. The growing prevalence of cargo bikes and scooters on these paths makes cycling speeds more unstable.

Solitary paths are attractive to all kinds of cyclists, including commuters, children, leisurely and sportive cyclists, and even joggers and pedestrians. Large speed differences between them increase the frequency of overtaking, leading to speed instability.

4.3. Intersections and turns

Intersections and turns strongly destabilise cycling speeds. Cycling at all three kinds of intersections is more likely than at uninterrupted roads to have unstable patterns, especially the V-shape and decrease patterns. Signalised intersections have the largest effects with odds ratios between 2.28 and 12.82, while roundabouts and unsignalised intersections have smaller and similar impacts. Similarly, cycling before and after intersections tends to fall into the V-shape pattern, with a stronger effect at signalised intersections. Logically, decrease patterns are more likely to happen before intersections, while increase patterns are frequent after intersections. A similar result was found for turns, which cause more unstable speeds, especially V-shape patterns. More decrease patterns were observed before turns, while more increase patterns were found after turns. In addition, left turns have slightly stronger effects than right turns.

The influence of intersections and turns is mainly related to safety. Road users meet each other at intersections, so cyclists tend to decelerate before and at intersections to avoid traffic accidents. These effects are stronger at signalised intersections as traffic volumes are higher and cyclists have to stop in the case of red lights. Signalised intersections also have more reversed V-shape patterns, because of catching yellow lights. Turns involve potential risks, so cyclists slow down before turns and speed up afterwords. Left turns have slightly larger effects on speed stability than right turns, as traffic is right-handed.

4.4. Land use, bridges, slopes and sunlight conditions

Compared with built-up areas, cycling speeds are relatively stable in other land use areas, especially green areas. Built-up areas have dense populations and high bicycle volumes, which cause more disturbances to cycling. In addition, pedestrians and cyclists are not fully separated in some built-up areas, making cycling speeds more unstable. By contrast, green areas are less crowded and consequently can support stable cycling speeds.

Expectedly, bridges, tunnels and slopes also cause speed instability, compared to flat roads. The effect of bridges is bigger than tunnels, and uphill slopes have greater effects than downhill slopes.

Bad sunlight conditions lead to more stable speeds, as cyclists tend to move cautiously under these conditions to avoid accidents by reducing speed variations.

5. Conclusion and discussion

5.1. Conclusion

Speed is a fundamental variable in traffic flow theory, but although speed changes constantly during bike rides, so far its stability has received limited attention. This study introduced the concept of cycling speed stability and investigated it by distinguishing a stable speed pattern and five patterns of instability, and then explaining them using infrastructural, environmental and temporal characteristics. The results show that stable and unstable speed patterns differ in their shares, average speeds and determinants. On average, the stable speed cycling accounts for half the trip distance. Stable patterns show higher speeds than unstable patterns. Cyclists tend to have relatively stable speeds during weekends and holidays, on roads without intersections and turns, in green areas and during twilight and night. Remarkably, bicycle streets and tracks improve speed stability compared to physically separated bike paths. The V-shape pattern (decrease followed by increase) is the most frequent unstable pattern, having the lowest speed and occurring relatively frequently at intersections and turns. Reversed V-shape, complicated unstable and especially decrease and increase patterns are relatively rare, mainly occurring at intersections, turns and built-up areas.

5.2. Discussion

There is little previous research on cycling speed and cycling speed stability. Nevertheless, the determinants in the present study confirm the results of route choice research. Determinants that were not favoured in route choice, such as intersections, turns, built-up areas and slopes (Buehler & Dill, 2016; Clarry et al., 2019), are highly similar to those responsible for interruptions and speed instability, suggesting that cyclists choose routes that are stable in terms of speed. One notable exception is that cycling on physically separated bicycle paths is less stable than on infrastructure with mixed traffic, such as bike streets, conflicting with many studies which found that cyclists prefer separate bicycle infrastructures because of safety, less interruption and smoothness (Broach et al., 2012). However, a study based on other data from the Netherlands (Yan et al., 2024) found a similar result that cycling speeds are higher on bike streets and bike tracks than on physically separate paths. This may be a specific Dutch effect related to the width of bike facilities and the distribution of bicycle volumes. Bike streets are wide, and cyclists on bike tracks can use car lanes occasionally, while physically separate paths are relatively narrow and busy. In addition, separate paths may be used a little more for leisure and exercise purposes, causing a big speed difference between cyclists. These characteristics lead to more interactions between cyclists, especially the overtaking, and cyclists may need to adjust their speeds more on these paths. It implies that the results do not necessarily mean that separate paths perform poorly in speed stability. So the results should be interpreted and applied with care.

Accurate GPS recordings and proper speed calculation are important for studying cycling speed stability. The data used in this study was verified by the Netherlands National Institute for Public Health and the Environment (RIVM) (Snuffelfiets, 2020), ensuring the location accuracy of tracking points. This accuracy was further reflected in the proximity of almost all the tracking points to the digital bicycle network of the Cyclists' Union (Fietsersbond). Still, a very small underestimation of speed might have occurred as the speed calculation was based on the Euclidean distance between two consecutive points. This mainly happens on curved routes, where the Euclidean distance is shorter than the actual distance, with sharper curves causing a bigger deviation. Consequently, even if cyclists maintain a constant speed through a turn, this phase would be detected as a V-shape pattern, and the effect of turns on speed instability will be slightly exaggerated. However, this error is negligibly small since V-shape patterns occur naturally at turns, where cyclists usually decelerate before turns and accelerate after turns (Yan et al., 2024). Euclidean distance only makes V-shape patterns more evident at turns, but the possibility of wrongly recognising other speed patterns as V-shape patterns is low.

5.3. Future research directions

To the best of our knowledge, this paper describes the first study on cycling speed stability, especially with a large GPS-based dataset. For further depth, we recommend the following:

First, although the current dataset is highly unique in the world, cycling data with a finer temporal and spatial resolution would allow an even deeper understanding. Cycling speed changes constantly, especially at intersections and turns. A smaller GPS tracking interval captures more details about speed changes (Ma & Luo, 2016) and helps to detect speed change patterns more accurately. In addition, lateral movements are frequent when cycling speeds are unstable, such as in the situation of overtaking, and a finer resolution can detect this information for better understanding speed (in)stability.

Second, we assumed that the width and bicycle volume on different bike lane types explain speed (in)stability, but they cannot be tested due to data unavailability. Further examination of these attributes is needed. Cycling comfort and safety issues raised by other bicycles should be considered in the design of bike lanes, and they can also be reflected in speed stability. By testing speed (in)stability on bike lanes with different widths and bicycle volumes, it can provide theoretical evidence for optimal widths to ensure comfortable and safe cycling.

Third, a deeper understanding is needed of the influence of other road users, especially cyclists. According to Guo et al. (2021), it can be assumed that cyclists adapt their speeds when cycling volumes increase, causing unstable speeds. This influence can be analysed from both macroscopic and microscopic perspectives. The macroscopic perspective can focus on density, such as the bicycle density at which cycling speeds start to be unstable and whether the bicycle density linearly influences overall speed stability. The microscopic direction, however, is mainly related to one cyclist's speed changes when meeting others, such as during overtaking situations. These speed changes may differ across cyclist groups (e.g. age, gender, bicycle types and trip purposes). In addition, one cyclist's behaviours may vary with the cyclist being overtaken.

Fourth, in this dataset, cyclists' characteristics were unavailable, but age, gender, preferences for speed and speed stability, cycling experiences and attitudes, relate to cyclists' perceptions (Heinen et al., 2010; Yan et al., 2024), and physical and mental capabilities (Bernhoft & Carstensen, 2008), all being expected to influence speed stability. In addition, some of these factors are correlated, having interaction effects on cycling speed stability. For example, years of cycling experience or the experience of traffic accidents would shape attitudes toward cycling, therefore influencing speed (in)stability. For bicycle types, electric bicycles provide cyclists with pedal assistance, so cyclists with e-bikes can maintain their speeds easily, but they can change their speeds quickly in situations, such as overtaking and at intersections. In addition, cyclists' route choices may also differ because of their bicycle types, resulting in differences in speed stability.

Fifth, self-selection may play a role. Cyclists may choose their residential areas, cycling routes, bicycle types, departure times and other factors to match their cycling preferences (Pinjari et al., 2008). For example, cyclists who prefer smooth cycling (e.g. racing bikes, elderly people) may cycle outside rush hours and on uninterrupted routes with few intersections and lower bicycle volumes. Those who are cautious may prefer separate lanes, which further influences their cycling speed stability.

Sixth, although it is plausible that cyclists prefer stable speeds over instability, the extent to which this is important for cyclists' comfort and related choice behaviour, such as cycling frequency and route choice, has not yet been investigated. Future research may explore whether stable speeds are important to cyclists, thereby supporting policies such as smart traffic lights and uninterrupted fast cycle paths.

Finally, in several countries, governments or knowledge institutes provide design guidelines for infrastructure (Schröter et al., 2021). It could be investigated how knowledge regarding cycling speed and stability could also be converted into guidelines for cycling infrastructure and related policies.

Cycling speed and its (in)stability are important attributes of cycling traffic flow, and an increasing number of studies examine cycling speed. However, cycling speed stability has hardly received attention in science, while there is increasing attention to this in policy and practice. The current study has explored speed stability, regarding its patterns, speed and share of different patterns, and their determinants, finding a considerable amount of unstable cycling speed, which mainly occurs at intersections, turns and on narrow bike lane types. It is beyond the scope of this study to examine how cyclists evaluate it, but it is reasonable to assume that they value it negatively and would therefore benefit from a smooth cycling network. More research is needed regarding the importance of cycling speed stability and its implications for planners.

CRediT authorship contribution statement

Hong Yan: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Conceptualization. **Kees Maat:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Bert van Wee:** Writing – review & editing, Supervision, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

Data availability

The authors do not have permission to share data.

References

Aarts, L., van Schagen, I., 2006. Driving speed and the risk of road crashes: a review. Accid. Anal. Prev. 38 (2), 215–224. https://doi.org/10.1016/j.aap.2005.07.004.

Adacher, L., Gemma, A., & Oliva, G. (2014). Decentralized spatial decomposition for traffic signal synchronization. *17th Meeting of the Euro Working Group on Transportation, Ewgt2014, 3*, 992-1001. https://doi.org/10.1016/j.trpro.2014.10.079.

AHN. (2020). *Actueel Hoogtebestand Nederland*. https://www.ahn.nl/.

Aminikhanghahi, S., Cook, D.J., 2017. A survey of methods for time series change point detection. Knowl. Inf. Syst. 51 (2), 339–367. https://doi.org/10.1007/s10115-016-0987-z.

Arnesen, P., Malmin, O.K., Dahl, E., 2020. A forward Markov model for predicting bicycle speed. Transportation 47 (5), 2415–2437. https://doi.org/10.1007/s11116-019-10021-x.

Bernhoft, I.M., Carstensen, G., 2008. Preferences and behaviour of pedestrians and cyclists by age and gender. Transportation Research Part F-Traffic Psychology and Behaviour 11 (2), 83–95. https://doi.org/10.1016/j.trf.2007.08.004.

Bian, Z., Zuo, F., Gao, J., Chen, Y., Pavuluri Venkata, S.S.C., Duran Bernardes, S., Ozbay, K., Ban, X.J., Wang, J., 2021. Time lag effects of COVID-19 policies on transportation systems: a comparative study of New York City and Seattle. Transp Res Part A Policy Pract 145, 269–283. https://doi.org/10.1016/j.tra.2021.01.019.

Broach, J., Dill, J., Gliebe, J., 2012. Where do cyclists ride? a route choice model developed with revealed preference GPS data. Transp. Res. A Policy Pract. 46 (10), 1730–1740. https://doi.org/10.1016/j.tra.2012.07.005.

Buehler, R., Dill, J., 2016. Bikeway networks: a review of effects on cycling. Transp. Rev. 36 (1), 9–27. https://doi.org/10.1080/01441647.2015.1069908.

Buehler, R., Pucher, J., 2021. *Cycling for sustainable cities*. MIT Press.

CBS. (2015). *Bestand Bodemgebruik*. https://www.cbs.nl/nl-nl/dossier/nederland-regionaal/geografische-data/bestand-bodemgebruik.

Choudhary, P., Imprialou, M., Ruina, N.R., Choudhary, I., 2018. Impacts of speed variations on freeway crashes by severity and vehicle type. Accid. Anal. Prev. 121, 213–222. https://doi.org/10.1016/j.aap.2018.09.015.

Clarry, A., Faghih Imani, A., Miller, E.J., 2019. Where we ride faster? Examining cycling speed using smartphone GPS data. Sustain. Cities Soc. 49. https://doi.org/10.1016/j.scs.2019.101594.

CROW-Fietsberaad. (2015). *Aanbevelingen fiets- en kantstroken*. Retrieved 19 June 2024 from https://www.fietsberaad.nl/Kennisbank/Aanbevelingen-fiets-en-kantstroken.

CROW. (2022). *Een fietspad moet voortaan minstens 2,30 meter breed zijn*. Retrieved 6th June 2024 from https://fietsberaad.nl/Kennisbank/Een-fietspad-moet-voortaan-minstens-2,30-meter-bre.

Dorcas Wambui, G., 2015. The power of the pruned exact linear time(PELT) test in multiple changepoint detection. Am. J. Theor. Appl. Stat. 4 (6). https://doi.org/10.11648/j.ajtas.20150406.30.

Eriksson, J., Forsman, Å., Niska, A., Gustafsson, S., Sörensen, G., 2019. An analysis of cyclists' speed at combined pedestrian and cycle paths. Traffic Inj. Prev. 20, S56–S61. https://doi.org/10.1080/15389588.2019.1658083.

Farah, H., Piccinini, G.B., Itoh, M., Dozza, M., 2019. Modelling overtaking strategy and lateral distance in car-to-cyclist overtaking on rural roads: a driving simulator experiment. Transportation Research Part F-Traffic Psychology and Behaviour 63, 226–239. https://doi.org/10.1016/j.trf.2019.04.026.

Flügel, S., Hulleberg, N., Fyhri, A., Weber, C., Ævarsson, G., 2019. Empirical speed models for cycling in the Oslo road network. Transportation 46 (4), 1395–1419. https://doi.org/10.1007/s11116-017-9841-8.

Frendo, T. (2010). The classification and analysis of 300 cycling crashes that resulted in visits to hospital emergency departments in Toronto and Vancouver.

Gibreel, G.M., Easa, S.M., Hassan, Y., El-Dimeery, I.A., 1999. State of the art of highway geometric design consistency. J. Transp. Eng. 125 (4), 305–313. https://doi.org/10.1061/(ASCE)0733-947X(1999)125:4(305).

Graham, R., 1998. The delaying effect of stops on a cyclist and its implications for planning cycle routes. In: Mathematics in Transport Planning and Control. Emerald Group Publishing Limited, pp. 237–246.

Guo, N., Jiang, R., Wong, S.C., Hao, Q.Y., Xue, S.Q., Hu, M.B., 2021. Bicycle flow dynamics on wide roads: Experiments and simulation. Transportation Research Part C-Emerging Technologies 125. https://doi.org/10.1016/j.trc.2021.103012.

Gustafsson, L., Archer, J., 2013. A naturalistic study of commuter cyclists in the greater Stockholm area. Accid. Anal. Prev. 58, 286–298. https://doi.org/10.1016/j.aap.2012.06.004.

Gutiérrez, J., González, R., Gómez, G., 1996. The European high-speed train network. J. Transp. Geogr. 4 (4), 227–238. https://doi.org/10.1016/s0966-6923(96)00033-6.

Heinen, E., van Wee, B., Maat, K., 2010. Commuting by bicycle: an overview of the literature. Transp. Rev. 30 (1), 59–96. https://doi.org/10.1080/01441640903187001.

Hoogendoorn, S.P., 2005. Unified approach to estimating free speed distributions. Transportation Research Part B-Methodological 39 (8), 709–727. https://doi.org/10.1016/j.trb.2004.09.001.

Huertas-Leyva, P., Dozza, M., Baldanzini, N., 2018. Investigating cycling kinematics and braking maneuvers in the real world: e-bikes make cyclists move faster, brake harder, and experience new conflicts. Transportation Research Part F-Traffic Psychology and Behaviour 54, 211–222. https://doi.org/10.1016/j.trf.2018.02.008.

Joo, S., Oh, C., Jeong, E., Lee, G., 2015. Categorizing bicycling environments using GPS-based public bicycle speed data. Transportation Research Part C-Emerging Technologies 56, 239–250. https://doi.org/10.1016/j.trc.2015.04.012.

Killick, R., Fearnhead, P., Eckley, I.A., 2012. Optimal detection of changepoints with a linear computational cost. J. Am. Stat. Assoc. 107 (500), 1590–1598. https://doi.org/10.1080/01621459.2012.737745.

Kircher, K., Ihlström, J., Nygårdhs, S., Ahlstrom, C., 2018. Cyclist efficiency and its dependence on infrastructure and usual speed. Transportation Research Part F-Traffic Psychology and Behaviour 54, 148–158. https://doi.org/10.1016/j.trf.2018.02.002.

Lee, J., Miller, H.J., 2018. Measuring the impacts of new public transit services on space-time accessibility: an analysis of transit system redesign and new bus rapid transit in Columbus, Ohio, USA. Appl. Geogr. 93, 47–63. https://doi.org/10.1016/j.apgeog.2018.02.012.

Li, C.M., Dai, Z.X., Peng, W.X., Shen, J.M., 2019. Green travel mode: trajectory data cleansing method for shared electric bicycles. Sustainability 11 (5). https://doi.org/10.3390/su11051429.

Ma, X.L., Luo, D., 2016. Modeling cyclist acceleration process for bicycle traffic simulation using naturalistic data. Transportation Research Part F-Traffic Psychology and Behaviour 40, 130–144. https://doi.org/10.1016/j.trf.2016.04.009.

Meijaard, J.P., Papadopoulos, J.M., Ruina, A., Schwab, A.L., 2007. Linearized dynamics equations for the balance and steer of a bicycle: a benchmark and review. Proceedings of the Royal Society a-Mathematical Physical and Engineering Sciences 463 (2084), 1955–1982. https://doi.org/10.1098/rspa.2007.1857.

Mohammed, H., Bigazzi, A.Y., Sayed, T., 2019. Characterization of bicycle following and overtaking maneuvers on cycling paths. Transportation Research Part C-Emerging Technologies 98, 139–151. https://doi.org/10.1016/j.trc.2018.11.012.

Nabavi Niaki, M.S., Saunier, N., Miranda-Moreno, L.F., 2018. Analysing cyclist behaviour at cycling facility discontinuities using video data. Transactions on Transport Sciences 9 (1), 3–17. https://doi.org/10.5507/tots.2018.006.

Pinjari, A.R., Eluru, N., Bhat, C.R., Pendyala, R.M., Spissu, E., 2008. Joint model of choice of residential neighborhood and bicycle ownership accounting for self-selection and unobserved heterogeneity. Transp. Res. Rec. 2082, 17–26. https://doi.org/10.3141/2082-03.

Rayaprolu, H.S., Llorca, C., Moeckel, R., 2020. Impact of bicycle highways on commuter mode choice: a scenario analysis. Environment and Planning B-Urban Analytics and City Science 47 (4), 662–677. https://doi.org/10.1177/2399808318797334.

Romanillos, G., Gutiérrez, J., 2020. Cyclists do better. Analyzing urban cycling operating speeds and accessibility. Int. J. Sustain. Transp. 14 (6), 448–464. https://doi.org/10.1080/15568318.2019.1575493.

Schepers, P., Theuwissen, E., Velasco, P.N., Niaki, M.N., van Boggelen, O., Daamen, W., Hagenzieker, M., 2023. The relationship between cycle track width and the lateral position of cyclists, and implications for the required cycle track width. J. Saf. Res. 87, 38–53. https://doi.org/10.1016/j.jsr.2023.07.011.

Schepers, P., Wolt, K.K., 2012. Single-bicycle crash types and characteristics. Cycling Research International 2 (1), 119–135.

Schleinitz, K., Petzoldt, T., Franke-Bartholdt, L., Krems, J., Gehlert, T., 2017. The German Naturalistic Cycling Study - Comparing cycling speed of riders of different e-bikes and conventional bicycles. Saf. Sci. 92, 290–297. https://doi.org/10.1016/j.ssci.2015.07.027.

Schröter, B., Hantschel, S., Koszowski, C., Buehler, R., Schepers, P., Weber, J., Wittwer, R., Gerike, R., 2021. Guidance and practice in planning cycling facilities in europe-an overview. Sustainability 13 (17). https://doi.org/10.3390/su13179560.

Schwab, A.L., Meijaard, J.P., Kooijman, J.D.G., 2012. Lateral dynamics of a bicycle with a passive rider model: stability and controllability. Veh. Syst. Dyn. 50 (8), 1209–1224. https://doi.org/10.1080/00423114.2011.610898.

Skov-Petersen, H., Jacobsen, J.B., Vedel, S.E., Alexander, S.N.T., Rask, S., 2017. Effects of upgrading to cycle highways-an analysis of demand induction, use patterns and satisfaction before and after. J. Transp. Geogr. 64, 203–210. https://doi.org/10.1016/j.jtrangeo.2017.09.011.

Small, K.A., 2012. Valuation of travel time. Econ. Transp. 1 (1–2), 2–14. https://doi.org/10.1016/j.ecotra.2012.09.002.

Snuffelfiets. (2020). https://snuffelfiets.nl/.

Strauss, J., Miranda-Moreno, L.F., 2017. Speed, travel time and delay for intersections and road segments in the Montreal network using cyclist Smartphone GPS data. Transportation Research Part D-Transport and Environment 57, 155–171. https://doi.org/10.1016/j.trd.2017.09.001.

Truong, C., Oudre, L., Vayatis, N., 2020. Selective review of offline change point detection methods. Signal Process. 167. https://doi.org/10.1016/j.sigpro.2019.107299.

Twisk, D., Stelling, A., Van Gent, P., De Groot, J., Vlakveld, W., 2021. Speed characteristics of speed pedelecs, pedelecs and conventional bicycles in naturalistic urban and rural traffic conditions. Accid. Anal. Prev. 150, 105940. https://doi.org/10.1016/j.aap.2020.105940.

Twisk, D.A.M., Platteel, S., Lovegrove, G.R., 2017. An experiment on rider stability while mounting: Comparing middle-aged and elderly cyclists on pedelecs and conventional bicycles. Accid. Anal. Prev. 105, 109–116. https://doi.org/10.1016/j.aap.2017.01.004.

Uijtdewilligen, T., Ulak, M.B., Wijlhuizen, G.J., Bijleveld, F., Dijkstra, A., Geurs, K.T., 2022. How does hourly variation in exposure to cyclists and motorised vehicles affect cyclist safety? a case study from a dutch cycling capital. Saf. Sci. 152. https://doi.org/10.1016/j.ssci.2022.105740.

Wolf, J., 2000. *Using GPS data loggers to replace travel diaries in the collection of travel data.* Georgia Institute of Technology.

Yan, H., Maat, K., van Wee, B., 2024. Cycling speed variation: a multilevel model of characteristics of cyclists, trips and route tracking points. Transportation. https://doi.org/10.1007/s11116-024-10477-6.

Zarindast, A., Poddar, S., Sharma, A., 2022. A data-driven method for congestion identification and classification. Journal of Transportation Engineering Part A-Systems 148 (4). https://doi.org/10.1061/Jtepbs.0000654.