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Cycling speed and weather: Roles of cyclist weather-sensitivity, spatial and infrastructural conditions

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ABSTRACT

Weather significantly influences cycling speed, with important influencing factors being physical effort, safety concerns and comfort. This influence can affect cycling behavior and ultimately cycling attractiveness. However, little evidence exists on how weather influences cycling speed. This study examines this influence, considering varied weather-sensitivity across people and the self-selection bias that some people avoid cycling during bad weather. It also explores cyclists and geographic heterogeneity, i.e. across cyclists and places. Using GPS-tracked cycling data and detailed weather data, a factor mixture model revealed different weather-sensitivity groups, and multilevel linear models with an autoregressive residual structure estimated the impact of weather components, weather-sensitivity groups and bicycle infrastructure on cycling speed. The results reveal three groups: weather-sensitive cyclists, who are sensitive to bad weather; less-weather-sensitive cyclists, who, in contrast, are less influenced by weather overall; and less-rain-sensitive cyclists, who are similarly less affected by weather, but are especially less sensitive to rain. These three groups do not differ in cycling speed. In addition, the influence of rain on cycling speed does not vary across groups after accounting for bicycle infrastructure, indicating no cyclist heterogeneity regarding the impact of rain on cycling speed. Snow, ice, twilight and darkness decrease speed, while fog increases it. Tailwinds increase speed, and headwinds decrease speed; wind shelter mitigates these effects by reducing wind exposure, indicating geographic heterogeneity. The findings are relevant for urban planning and infrastructure design to reduce the negative impacts of weather.

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1. Introduction

Weather influences mobility, in particular its daily variation (Liu et al., 2017), with cycling, an active and weather-exposed mode, being affected most (Faber et al., 2022; Heinen et al., 2011). Bad weather conditions discourage cycling, which is partly offset by cars (Jonkeren, 2020). Therefore, an increasing number of studies examine the influence of weather on cycling behavior. So far, most studies focus on mode choice, namely the choice between cycling and other transportation modes (De Kruijf et al., 2021). However, cycling speed is hardly studied, although it can be assumed to play a role in weather-related cycling behavior.

We hypothesize that weather affects cyclists' physical and mental states in three aspects, namely effort required, comfort, and safety concerns, which are related to cycling speed and, ultimately, travel time (Figure 1).

First, several weather components, particularly wind, affect the resistance a cyclist is subjected to. Generally, headwinds require extra effort and decrease cycling speed, while tailwinds provide assistance, reducing required effort and increasing speed (Yan et al., 2025). However, cyclists may feel the need to adapt to the resistance changes and adjust their effort in response to wind conditions, perhaps even so that the desired speed can be maintained. For example, as Pérez Castro et al. (2025) observed, light wind does not significantly affect cycling speed because cyclists compensate by adjusting their effort.

Second, weather conditions can cause discomfort (e.g. due to stiff muscles at low temperatures or sweating at high temperatures (Schulze et al., 2015)) that limits physical performance and therefore speed. People may also ride faster to shorten their exposure to uncomfortable weather conditions, such as rain (Fietstelweek, 2017; Yan et al., 2025). Not only is discomfort directly experienced, but the prospect of it can also have an impact, for example, by cycling faster to avoid predicted precipitation.

Third, because of safety concerns under conditions of snow, ice, and rain, cyclists become cautious and often slow down (Shoman et al., 2023). Conversely, cyclists may attempt to reach shelter more quickly during thunderstorms to reduce lightning exposure (NOAA, 2025).

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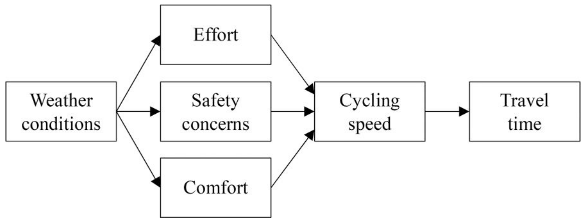

Figure 1. Conceptual model of the influence of weather on cycling speed.

Ultimately, the changes in cycling speed due to weather conditions affect travel time (assuming constant origins, routes and destinations of cycling trips). As travel time is considered a disutility, especially for commuting trips (Koster & Koster, 2015), some weather conditions tend to weaken the competitive position of cycling relative to motorized modes. This may also shape the overall perception of cycling; for example, bad weather conditions are not suitable for cycling anyway.

However, we do not assume that this applies to all cyclists to the same extent. Cyclists have different feelings toward effort, comfort and safety, due to variations in attitudes, physical conditions, cycling experiences and available cycling equipment. Moreover, they differ in the perceptions of what they consider good and bad weather (Spencer et al., 2013) and the extent to which they accept bad weather conditions for cycling (Nordbakke & Olsen, 2019). Consequently, weather-sensitivity is expected to vary between cyclists, and they can therefore be classified into different clusters of weather-sensitivity. For example, experienced cyclists are expected to be less affected by precipitation, and consequently cycle more during rain than less experienced cyclists (Motoaki & Daziano, 2015).

Furthermore, geographic heterogeneity is assumed, as spatial objects can change the microclimate. For example, buildings and forests reduce wind speed on their downwind side (Mittal et al., 2018). However, research on both cyclist and geographic heterogeneity is limited, as noted and examined by Nordbakke and Olsen (2019) and Helbich et al. (2014).

Climate change would further exacerbate the negative effects of weather on cycling speed. The climate tends to be warmer, more windy and rainy, and extreme weather conditions, such as heat waves, cold waves, and intense precipitation, become more frequent (Capua & Rahmstorf, 2023). For these reasons, understanding the influence of weather on cycling speed becomes increasingly relevant for cycling.

We thus hypothesize that the effect of weather on cycling speed may be substantial, which may also have consequences for mode (and maybe destination) choice, but also note that the literature offers little insight into this. However, it is imperative to gain knowledge on this, which can help urban and infrastructure planners develop policies to protect cyclists from bad weather conditions and mitigate speed losses and discomfort.

The current study seeks to gain insights by testing the effect of weather conditions on cycling speed. We control for weather-sensitivity, i.e. potential cyclists are missing due to bad weather conditions (self-selection) and their speeds are differentially affected by weather (cyclist heterogeneity). We also control for geographic heterogeneity, because of the shelter that land use can provide. To this end, over 65,000 GPS-based bicycle trips from 224 cyclists are analyzed. The GPS-based dataset provides location and time stamps, allowing detailed speed calculation. Time and location stamps also allow data on the weather conditions and physical environment to vary along a route by linking precise data to each tracking point. Factor mixture models (FMM) are estimated to reveal unobserved weather-sensitivity groups. Three-level linear models with an autoregressive residual structure are estimated to examine the influence of weather and other factors from the cyclist, trip and point levels on cycling speed.

The remainder of this paper is structured as follows. Section 2 briefly reviews the literature and outlines research aims and assumptions. Section 3 describes the data and methods, and Section 4 illustrates key results, followed by conclusions and discussions in Section 5.

2. Literature review

2.1. Overview of the literature review

This section describes (1) cyclist heterogeneity under various weather conditions, (2) the direct influences of weather on cycling speed, and (3) the influence of other factors on cycling speed. It addresses the impact of weather on cycling demand and cyclist heterogeneity, and demonstrates weather-sensitivity among cyclists, which is represented in the present study as weather-sensitivity groups. This is followed by a discussion of the still-limited evidence on the direct influence of weather on cycling speed. Then, the influence of other factors on cycling speed is briefly summarized.

2.2. Weather's effects on cycling behavior in general

Various weather conditions influence cycling, and the most examined components are precipitation, wind and temperature (Böcker et al., 2013; Koetse & Rietveld, 2009; Liu et al., 2017). In general, good weather conditions, being sunny and warm, calm or with light winds, encourage commuting by bicycle, more bicycle trips and longer bicycle trip distances (De Kruijf et al., 2021; Helbich et al., 2014; Nahal & Mitra, 2018).

Precipitation (Böcker & Thorsson, 2014; Helbich et al., 2014), especially snow (Liu et al., 2015b), strongly reduces cycling usage, and its influence increases with precipitation volume/intensity (Böcker et al., 2015; Tin Tin et al., 2012) and duration (Heinen et al., 2011). In addition, cycling is influenced by the expected precipitation in the near future (Zhao et al., 2018), such as not cycling in the morning because of expected rain in the afternoon (De Kruijf et al., 2021). Wind also negatively affects cycling (Bjørnarå et al., 2023; Helbich et al., 2014; Zhao et al., 2019), and strong winds have a bigger influence (Böcker & Thorsson, 2014). Temperatures have a positive or bell-shaped effect on cycling usage (De Kruijf et al., 2021; Heinen et al., 2011; Liu et al., 2015a, 2015b; Zhao et al., 2019), depending on climate zones. Most evidence indicates that the most attractive temperature for cycling is around 25°C (Böcker et al., 2019; Böcker & Thorsson, 2014; Helbich et al., 2014).

A few studies have used comprehensive weather indicators, such as physiologically equivalent temperature (PET), to capture overall thermal conditions. For example, Brandenburg et al. (2007) found a positive relationship between PET and bicycle usage, while El-Assi et al. (2017) found that higher perceived temperature is associated with increased bicycle demand.

2.3. Cyclist heterogeneity

The influence of weather on cycling varies across individuals (Nordbakke & Olsen, 2019). First, people have different perceptions of the weather. For example, some cyclists do not negatively evaluate wind and rain but regard them as refreshing and helpful (Spencer et al., 2013). Besides, the acceptance levels of cycling under the perceived bad weather depend on cyclists' physical condition, experience, and cultural context. For example, men and young adults are less influenced by precipitation and cold weather than women and older people (Amiri & Sadeghpour, 2015; Bergström & Magnusson, 2003). Experienced and skilled cyclists are less affected by snow and rain than inexperienced cyclists (Motoaki & Daziano, 2015). Heinen et al. (2011) found that occasional bicycle commuters cycle when the weather is nice, while frequent bicycle commuters cycle unless the weather conditions are too bad. Cultural contexts also play a role; Hudde (2023) found that the mobility culture makes cycling less affected by winter conditions in Dutch cities compared to German cities. Furthermore, the negative effects of rain or wind can be mitigated by wearing a raincoat or using an electric bicycle (De Kruijf et al., 2021; Rietveld & Daniel, 2004; Spencer et al., 2013). Overall, these findings show the existence of different weather-sensitivity groups.

2.4. The influence of weather on cycling speed

Only a few studies have tested the influence of weather on cycling speed, mainly focusing on precipitation. Snow and snowy surfaces decrease cycling speed significantly by around 15% due to cyclists' caution to avoid possible risks, such as slipping (Shoman et al., 2023). Rain also affects cycling speed; Romanillos and Gutiérrez (2020) found that cycling during cloudy and rainy days is slower than on sunny days, and this decrease in speed is bigger on mixed-use roads than on exclusive bicycle paths. However, other studies found an opposite result; using a Dutch dataset (Fietstelweek, 2017), a higher cycling speed was observed in rainy or foggy conditions than the average cycling speed (17.8 versus 17.0 km/h). Yan et al. (2025), also using Dutch data, confirmed that light-medium rain (0–5 mm/h) increases cycling speed by 0.9 km/h since cyclists try to reduce the exposure to this uncomfortable situation, while the positive effect does not exist for heavy rain (>5 mm/h), perhaps because safety issues and discomfort prevent faster cycling. Maurer et al. (2025) found an increased cycling speed during both light and heavy rain in Switzerland, and this result applied to all bicycle types; however, their rainfall intensity was classified by the rain duration within an hour instead of the rainfall volume per unit time.

Other examined weather components include wind and temperature. Wind is highly related to the resistance during cycling and influences the effort needed. Yan et al. (2025) found that strong tailwinds (> 5.5 m/s) increase cycling speed by 1.6 km/h, and light tailwinds (1.5–5.5 m/s) have a smaller effect at 0.6 km/h, but headwinds do not influence cycling speed. Pérez Castro et al. (2025) observed no cycling speed changes due to light winds (< 3 m/s), as cyclists may be capable and willing to compensate for wind by changing their effort. Temperature influences the body heat balance and muscle conditions, and therefore cyclists' performance (Schulze et al., 2015). Strauss and Miranda-Moreno (2017) found that a temperature of $10-20$°C increases cycling speed by 0.15 km/h compared to lower or higher temperatures.

It follows from the above that weather influences physical comfort (rain and temperature), safety concerns (snow) and effort (wind), and therefore cycling speed is affected.

2.5. Other factors affecting cycling speed

Cycling speed is also affected by cyclists' characteristics, bicycle types, bicycle infrastructure and land use. We refer to Yan et al. (2025) for a comprehensive overview of their effects. In brief, young, male and experienced cyclists ride faster. Electric and sportive bicycles have a higher speed than city bicycles. Regarding bicycle infrastructures, cycling on physically separated paths is faster than on shared roads, despite several opposite findings. Intersections, turns, curved roads and bad surfaces decrease cycling speed. Cycling uphill is slow, while cycling downhill is fast. In areas with dense populations or buildings, such as city centers, urban areas and built-up areas, a lower speed is observed than in rural areas.

2.6. Gaps, aims and assumptions

Only a few studies address the influence of weather on cycling speed, with a limited focus on precipitation and no in-depth study yet on a broad range of weather components. Therefore, the present study aims to understand the extent to which different weather components influence cycling speed, controlling for bicycle infrastructure, land use and trip situations. We depart from four assumptions. First, cyclists are not equally sensitive to weather or specific weather aspects, so a distinction is assumed between weather-sensitivity groups. At first glance, cyclists who are less sensitive to weather tend to be experienced and strong, cycling faster. Second, self-selection is expected: weather-sensitive cyclists are less inclined to cycle in bad weather, resulting in a higher representation of less-sensitive cyclists during bad weather. Without accounting for this weather-

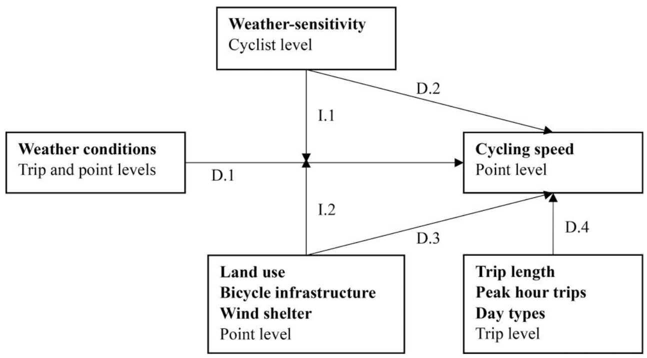

Figure 2. The model specification for the influence of weather on cycling speed.

based self-selection, it is possible to misattribute the effect of weather-sensitivity groups on cycling speed to weather conditions, causing misleading results. Third, it is assumed that the speeds of cyclists with varied weather-sensitivities are influenced differently by the same weather conditions, showing cyclist heterogeneity. Fourth, land use is assumed to influence the local weather conditions and moderate the effect of weather on cycling speed, which is the geographic heterogeneity.

3. Data and method

3.1. Overview of method

A GPS-tracked dataset of cycling trips is used, in which each cyclist makes multiple trips, and a trip consists of a series of tracking points (Section 3.2.1). A factor mixture model is estimated to distinguish weather-sensitive groups (Section 3.3). Next, due to a hierarchical time-series data structure (cyclist, trip and tracking point levels), multilevel models with an autoregressive residual structure (Section 3.4) are estimated to account for the dependence of observations.

Figure 2 shows the assumed effects of independent variables on cycling speed, indicating the levels at which they are measured. All variables directly influence cycling speed (arrows D.1 to D.4). Controlling for self-selection, in which weather-sensitivity determines the weather conditions under which cycling takes place, would require stated choice data, namely whether a trip would have been made in bad weather, and if so, which alternative mode of transport would have been chosen. The current dataset does not have this detailed information. Therefore, this study controls partially for self-selection by including weather-sensitivity groups (arrow D.2), which capture both people's physical abilities and their inclination to cycle under various weather conditions. An interaction term between weather-sensitivity groups and weather (arrow I.1) is considered to capture cyclist heterogeneity. Similarly, a wind shelter indicator is introduced (Section 3.2.4) to represent geographic differences. Wind shelter influences local wind conditions and, consequently, cycling speed. However, data on the microscopic wind environment around the wind shelter are unavailable, so we included an interaction term between shelter and ambient wind (arrow I.2) as a proxy to examine geographic heterogeneity. Although the local environment interacts with many weather conditions, wind shelter and wind are chosen because of evident interaction. Bicycle types and cyclist characteristics are assumed to have an impact, but they are not available in the dataset.

3.2. Data, study area and variables

3.2.1. Cycling data and study area

Cycling data is derived from the Sniffer Bike project (Snuffelfiets, 2020), which aims to support research to expand knowledge about cycling and the physical environment. The project started in June 2019 and is still ongoing. Cyclists make multiple trips over a long time, ensuring enough weather variability. Their bicycles are equipped with a sensor kit with GPS functions. The GPS device registers the position of bicycles every 13 s, making it possible to capture detailed variation in cycling speed and cycling route conditions. Although it is a rich and longitudinal dataset, it is also limited because respondents participate anonymously, so the characteristics of participants and bicycles are not registered. Participants were recruited from municipalities, resident groups and regional communities. They may not fully represent Dutch cyclists, but we do not expect a systematic self-selection bias in weather conditions.

The data used in the present study is a subset taken from January 2021 to October 2023; data before 2021 was excluded to reduce COVID-19's influence. During this period, 267 cyclists registered 96,413 bicycle trips. The data was first filtered to remove tracking points in stationary phases and trips with high-speed outliers or short distances. If ten or more continuous tracking points (lasting more than 2 min) have a speed below 5 km/h, they were regarded as stationary phases, such as a stopover for shopping, and removed. Trips with an average speed over 45 km/h are less likely to be made by cycling, so they were deleted. Also, trips shorter than 500 meters were removed, as their speed is more likely to be affected by stop-and-go movements than by weather, and the speed calculation tends to involve more measurement errors. Then, 40 cyclists making fewer than ten trips were excluded from sensitivity detection (see Section 3.3), as it is not likely to detect accurate weather-sensitivity of cyclists with few trips. Furthermore, some trips outside the study area or lacking infrastructure information were excluded from modeling, which removed three cyclists. The final dataset comprises 224 cyclists who made 65,122 rides, resulting in 5,260,281 tracking points.

The study area is centrally located in the Netherlands and includes the province of Utrecht and its adjacent municipalities (Figure 3). The city of Utrecht accounts for a quarter of all tracking points, and the number of tracking points of municipalities decreases with increasing distance from Utrecht. The central city, namely Utrecht, has one of the best bicycle infrastructure networks in the Netherlands (Schering et al., 2022), with 46% of trips made by bicycles (De Haas & Hamersma, 2020). This area has a marine climate with relatively cool summers, mild winters and frequent precipitation. Between 1991 and 2020, the De Bilt

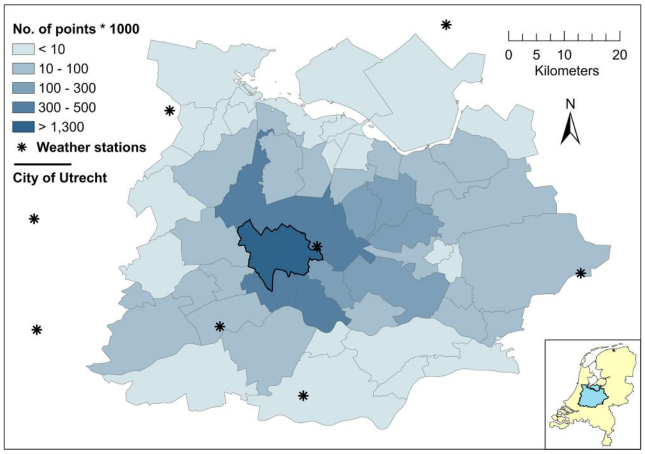

Figure 3. Study area, weather stations and tracking points distribution across municipalities.

weather station, the most centrally located station of the Royal Netherlands Meteorological Institute (KNMI) in the study area, recorded an average annual temperature of 10.3°C and precipitation of 893.9 mm. However, 2021 to 2023 were warmer (11.3°C) and rainier (1,032 mm) than usual (KNMI, 2024b). During this period, the Netherlands experienced a wide range of weather conditions (KNMI, 2024a), such as the wettest and warmest year (2023), the record wet October (2023) since 1906 and the heaviest storm and wind (February 2022) since 1990.

3.2.2. Speed and trip length

The cycling speed per tracking point was calculated by dividing the distance and the duration between two consecutive points, derived from their latitudes, longitudes, and time stamps. Trip length is the sum of the distances between all consecutive pairs of tracking points within the trip.

3.2.3. Weather data and related variables

The finest and most accurate weather dataset from KNMI was chosen to match the constantly changing cycling speeds. It is recorded by eight automatic weather stations in the study area (Figure 3). The weather dataset consists of four basic weather components (temperature, humidity, precipitation intensity and wind speed), which are recorded every 10 min, and five other weather components (snow, ice occurrence, fog, thunder and sunshine), recorded hourly. Light conditions based on sun positions are regarded as a weather-related condition and calculated using the time and location of tracking points.

Some studies have examined the impact of comprehensive thermal indicators, such as perceived temperature and physiologically equivalent temperature, on travel behavior (e.g. Brandenburg et al., 2007), considering that these indicators can directly reflect individuals' thermal perception (El-Assi et al., 2017). However, because they are calculated from multiple meteorological variables, it is difficult to disentangle the influences of individual components from the overall effect. This distinction is especially important for policy, because individual weather components can be linked more directly to specific environmental interventions, such as wind shelter. Therefore, this study focuses on individual weather components.

Weather variables were considered at the point or trip levels, dependent on the weather data resolution, the weather variability and the purpose of the variable. Specifically, the precipitation and wind conditions during the trip are point-level variables, meaning that their values are supposed to change within a trip. The reason is that they are recorded every ten minutes and can change suddenly, especially apparent wind that changes with the cycling direction. Other weather variables at the trip level are assumed to be constant for the entire trip. Although temperature and humidity are recorded every ten minutes, they hardly change during a bicycle trip in the Netherlands, so they are considered trip-level variables. This also applies to light conditions based on sun positions. The rain condition within half an hour after the trip aims to understand cyclists' responses to the near future weather, which is fixed for one trip. Many people in the Netherlands check rain forecasts, such as on Buienradar, before making a trip, especially when rain is highly likely (Engebretsen & Kennedy, 2020). Other variables, including snow, ice occurrence, fog, sunshine and thunder, are available hourly and can only be trip-level variables. Tracking points obtained weather data, except for daylight and rain conditions after trips, from the closest timestamp of the nearest station. Point-level variables use these values directly, while trip-level variables take the values from the mid-time tracking point of trips.

Precipitation was regarded as a binary variable: rain and no rain[1]. Wind was divided into seven categories: no wind, strong headwind, strong crosswind, strong tailwind, light headwind, light crosswind and light tailwind, based on the wind speed and the direction difference between wind and cyclists' movement. The definition of wind speed is strong ($> 5.5\ m/s$), light ($1.5-5.5\ m/s$) and no wind ($< 1.5\ m/s$), while the direction categories are tailwind (direction difference $<67.5°$), crosswind ($67.5° - 112.5°$) and headwind ($>112.5°$). Temperature was defined as cold ($< 10°C$), moderate/warm ($10-25°C$) and hot ($> 25°C$). Humidity also has three categories: dry ($< 70\%$), moist ($70\% - 90\%$) and wet ($> 90\%$). Light conditions, depending on the position of the sun, were divided into three classes: daylight with the sun above the horizon (between sunrise and sunset), darkness with the sun more than 18° below the horizon (between astronomical dusk and astronomical dawn) and twilight with the sun 0-18° below the horizon (between sunset and astronomical dusk as well as between astronomical dawn and sunrise). A daily based time for sun position was used. Sunshine duration is between 0 and 1, showing the share of time with sunshine during the weather-recorded hour. Snow, ice occurrence, fog, and thunder are binary variables, showing whether or not the specific weather condition exists. The near future rain condition is labeled as "yes" if

[1] Rain can be classified into detailed categories based on intensity, but there are few observations during heavy rain, and these come from only a few cyclists. Therefore, the inclusion of such a classification in the models tends to produce biased results, so a binary variable was used instead.

there is rain within half an hour after the trip. However, the near future rain condition is highly correlated to the precipitation during the trip, showing collinearity, so it was not included in the final analysis.

3.2.4. Wind shelter

Objects on the ground, such as trees and buildings, can influence the wind. Since detailed building information is available (3DBAG, 2023), the wind shelter caused by buildings was calculated. The location-specific wind conditions around buildings (speed and direction) are complex (Coceal & Belcher, 2005), and it is beyond the scope to involve all details. Therefore, a simplified calculation was adopted by considering the wind shelter only at the leeward side of buildings, where the low wind-speed zone mainly exists (Blocken & Carmeliet, 2004; Bottema, 1993).

The low wind-speed zone extends from the leeward wall of a building to the reattachment line, where the wind reattaches to the ground (Blocken et al., 2011). Its length, referred to as the reattachment length (L_R), is positively related to the building height (H) (Mittal et al., 2018). However, the literature found a wide range of L_R/H ratio, from 0.8 (Liu & Niu, 2016) to 8 (Bottema, 1993). The current study takes 1.25; if the distance between a tracking point and the leeward wall of the building is smaller than 1.25 times the building height, this point is considered to be in the shelter area. This conservative ratio of 1.25 ensures that the wind speed in the defined shelter area is clearly lower than the approach wind. Besides the height, a greater extent of the lateral area covered by upwind buildings enhances wind speed reduction (Mittal et al., 2018). It means that a tracking point with longer adjacent routes within the shelter area receives a stronger shelter effect.

All considered, the shelter value for a tracking point was calculated as follows. First, 25 virtual points spaced one meter apart along the cycling route were chosen before and after a tracking point. Then, it was checked whether the tracking point and virtual points are in the shelter area. Third, the share of points within the shelter area was calculated as the final shelter effect for the tracking point. So, the shelter effect is a continuous variable, ranging from zero to one, with zero meaning no shelter and one meaning the strongest shelter effect (full shelter).

3.2.5. Land use, bicycle infrastructure and slope

Land use, bicycle infrastructure and slope were calculated based on the locations of tracking points, which are the point-level variables.

Land use data is derived from the Bestand Bodemgebruik 2015 (CBS, 2015). The dominant land-use type within a 50-meter buffer of a tracking point was regarded as its land-use type. The original 13 types were classified into five types: built-up (residential, work, shopping, cultural facilities, public amenities), semi built-up (buildings and paving for non-daily uses), transport (e.g. airports, railways, main road network, parking lots, bus stations), industry and nature areas.

Bicycle infrastructure attributes are derived from the Cyclists' Union (Fietsersbond, 2018), including bike lane types, intersections, turns, bridges and tunnels. These attributes from the nearest network were linked to tracking points. Six bike lane types were distinguished: pedestrian areas, residential roads without bicycle facilities, bike tracks referring to on-road bicycle lanes, separated from motorized traffic by road markings or different pavements, bike streets where motorized vehicles are allowed but bicycles have priority (Rivera Olsson & Elldér, 2023), bike paths along roads that are physically separate from motorized traffic, and solitary bike paths independent of main roads. Intersections were classified into intersections with traffic lights, intersections without traffic lights and roundabouts. Based on this, the road within 30 meters of an intersection was classified as before/after intersections with/without traffic lights, depending on the cycling direction. Similarly, before/after right/left turns were recognized if a tracking point is within 30 meters of a turn, and the turn exceeds 80°. Bridges and tunnels were categorized as bridges, tunnels and regular roads.

Slope was calculated with the altitude from a 0.5 meter resolution altitude map of the Netherlands (AHN, 2020). First, all tracking points were assigned the elevation value from the pixel where they are located. Then, the slope was calculated based on the elevation difference and the distance between two continuous tracking points. Finally, the slope value was categorized into uphill (slope $> 2°$), flat road ($-2° \leqslant$ slope $\leqslant 2°$), and downhill (slope $< -2°$).

3.2.6. Peak hours and day types

Two time-related variables were assessed at the trip level based on the mid-trip time. Peak hours were divided into morning peak hours (6:30 – 9:00), evening peak hours (16:00—18:30), and off-peak hours. For the full-day types, we distinguished weekdays, weekends and holidays.

3.3. Cyclist weather-sensitivity detection

Following the literature, it is assumed that the underlying structure of people's weather-sensitivity is simultaneously categorical and continuous. First, distinct groups exist regarding the acceptance of weather conditions (Nordbakke & Olsen, 2019). Some people may hardly cycle during bad weather, while others are less influenced by weather (De Kruijf et al., 2021; Hudde, 2023). In addition, some individuals are less sensitive to specific weather conditions. For example, individuals do not avoid cycling in the rain because they wear raincoats or regard rain as refreshing (Spencer et al., 2013). These people are possibly less sensitive mainly to rain, while other weather components influence them to the same extent as other cyclists. Thus, categorical weather-sensitivity groups are distinguished. Second, many studies have found a linear relationship between cycling usage and weather components, such as precipitation intensity (Böcker et al., 2015; Tin Tin et al., 2012), wind speed (Böcker & Thorsson, 2014) and temperature (Liu et al., 2015a; Zhao et al., 2019). This suggests that, in general, people from high to low sensitive levels gradually stop cycling as weather conditions worsen, indicating a continuous structure in weather-sensitivity. The assumption that sensitivity can be described both categorically and continuously forms the theoretical basis for distinguishing weather-sensitivity groups.

Factor mixture model (FMM) was estimated to recognize unobserved weather-sensitivity groups. It combines latent class analysis and factor analysis by introducing a hybrid structure of categorical and continuous latent variables (Clark et al., 2013; Lubke & Muthén, 2007; Morin & Marsh, 2015). A categorical latent variable classifies individuals into different weather-sensitivity groups, and simultaneously, continuous latent variables, namely latent factors, capture the ordered sensitivity of individuals within a class. The reason not to choose latent class analysis, which is widely used in travel behavior analysis (Kim & Mokhtarian, 2023; Molin et al., 2016), is its assumption of local independence, implying that the observed indicators within a class should be fully statistically uncorrelated (Bauer, 2022; Vermunt & Magidson, 2002). In this study, weather-related factors were chosen as indicators, as described below, so an ordered sensitivity dimension within a class implies the existence of local dependence; for example, rain often accompanies a decline in temperature.

For this purpose, five class indicators were calculated from raw weather data for each cyclist, including the average monthly standard deviation of temperature (°C), humidity (%), precipitation intensity (mm/h) and wind speed (m/s), as well as the ratio of cycling distance during rainy conditions to the total cycling distance (hereafter referred to as the rain length ratio).

The standard deviation illustrates the variation of a weather component under which a cyclist chooses to cycle, with a higher value meaning a lower sensitivity to the weather component. To reduce the bias from seasonal weather variation and cyclists' unequal participation lengths in the project, the four standard deviation indicators were first calculated per calendar month and then averaged for the cyclist. In this dataset, 41 participants stayed in the project for less than four months but may also cycle during other periods. By contrast, 32 cyclists had cycling records for more than 30 months. If the standard deviation was calculated with all trips of a cyclist, the short-term participants are likely to have a lower standard deviation than those in the project for more than one year. This does not necessarily mean that the short-term participants are more sensitive to weather than others. Therefore, the average monthly standard deviation was used.

The rain length ratio shows sensitivity to rain, and a higher ratio means low sensitivity to rainfall. This ratio is intended to reduce the influence of extreme rainfall, which can significantly increase the standard deviation and possibly mislead the result. Unlike the standard deviation indicators, the rain length ratio is less affected by cyclists' participation lengths, so it was calculated with all trips. The length ratios for other weather components were not included because the difference between their usual and extreme values is relatively small. In addition, they are more predictable than rain, allowing cyclists to adjust their travel decisions in advance.

The standard deviation of weather component w for cyclist c in the i^{th} month is denoted by SD_{wci}, and weather components include temperature, humidity, precipitation intensity and wind speed. The SD_{wci} of temperature and humidity was calculated based on the number of trips during the i^{th} month, as they are trip-level variables and assumed to be constant within a trip. It was calculated as:

$$SD_{wci} = \sqrt{\frac{\sum_{r=1}^{R_{ci}} (x_{wcir} - \mu_{wci})^2}{R_{ci}}} \tag{1}$$

where R_{ci} is the trip number made by cyclist c in the i^{th} month, x_{wcir} is the weather value of ride r, and μ_{wci} is the average weather value of all rides of cyclist c during this month.

In contrast, the SD_{wci} of wind speed and precipitation intensity was calculated from the number of tracking points and their values at each tracking point during the i^{th} month, as their values are supposed to change during a ride. It was expressed as:

$$SD_{wci} = \sqrt{\frac{\sum_{p=1}^{P_{ci}} (x_{wcip} - \mu_{wci})^2}{P_{ci}}} \tag{2}$$

where P_{ci} is the tracking point number recorded by the cyclist c in the i^{th} month. Correspondingly, x_{wcip} and μ_{wci} are the value at the tracking point p and the average value of all points during this month, respectively.

Then, the average monthly standard deviation (SD_{wc}) is calculated as:

$$SD_{wc} = \frac{\sum_{i=1}^{n} SD_{wci}}{n} \tag{3}$$

where n is cyclist-specific, representing the number of months a cyclist has participated in the project.

The calculation of the rain length ratio is:

$$L_c = \frac{\sum_{r=1}^{R_c} \sum_{p \in rain(r)} D_{rp}}{\sum_{r=1}^{R_c} \sum_{p=2}^{P_r} D_{rp}} \tag{4}$$

where L_c is the rain length ratio for cyclist c, R_c is the total trip number made by cyclist c, P_r is the total tracking point number in ride r, $rain(r)$ is the set of tracking point in ride r recorded during rain, and D_{rp} is the distance between point p in ride r and its previous point.

To estimate the FMM, cyclists with fewer than ten recorded trips were excluded, as based on so few trips, an accurate weather-sensitivity pattern cannot be detected. This reduced the dataset by 40 cyclists to 227. FMM allows the factor structure (parameters including factor mean, variance, intercept and loading) to vary across classes (Clark et al., 2013). More varied parameters indicate greater differences in the factor structure across classes, resulting in a less restrictive model. For example, a varied factor variance allows samples to spread differently across classes. In real datasets, it is uncommon for the factor structure to be identical across classes. However, the best model variation for the current dataset is unclear, so four FMM variations were estimated, each allowing one additional parameter (factor mean, variance, intercept and loading) to vary across classes. All variations were estimated with two or more latent classes and one or more factors. FMM results depend on the starting values of the parameters, and some values lead to log-likelihoods being only a local maximum. To reach the global maximum, a large set of 5,000 random starting values was chosen, and the models were estimated twice to verify result consistency. Mplus 8.5 (Muthén & Muthén, 1998–2024) was used.

3.4. Multilevel modelling

Multilevel models were estimated to explore weather's influence on cycling speed, using the mixed command in Stata 19. The models include random intercepts for cyclists and trips; in addition, an autoregressive residual structure at the tracking point level is specified. This structure fits the current cycling dataset: cyclists make multiple trips, trips consist of a series of tracking points, and speeds at consecutive tracking points are correlated. A random intercept for each cyclist allows for individual baseline cycling speed, which accounts for inherent differences among cyclists, for example, some being naturally faster or slower than others. Likewise, random intercepts at the trip level reflect inherent differences between various trips of a cyclist. An autoregressive residual structure accounts for serial correlation between consecutive tracking points, preventing underestimation of standard errors (Luo et al., 2021). In other words, multilevel models with an autoregressive residual structure ensure reliable statistical inference.

Such a model for a single observation, y_{ctp}, the speed at point p in trip t of cyclist c, can be expressed as:

$$y_{ctp} = \beta_0 + \boldsymbol{X}_c\boldsymbol{\beta}_c + \boldsymbol{X}_{ct}\boldsymbol{\beta}_{ct} + \boldsymbol{X}_{ctp}\boldsymbol{\beta}_{ctp} + b_{0c} + b_{0ct} + \varepsilon_{ctp} \quad (5)$$

$$\varepsilon_{ctp} = \rho\varepsilon_{ct,p-1} + \mu_{ctp}, \mu_{ctp} \sim N(0, \sigma^2) \quad (6)$$

where the fixed effect is $\beta_0 + \boldsymbol{X}_c\boldsymbol{\beta}_c + \boldsymbol{X}_{ct}\boldsymbol{\beta}_{ct} + \boldsymbol{X}_{ctp}\boldsymbol{\beta}_{ctp}$, representing the influence of variables at three levels. $\boldsymbol{X}_c$ is a vector of cyclist-level variables with $\boldsymbol{\beta}_c$ being the corresponding vector of coefficients. $\boldsymbol{X}_{ct}\boldsymbol{\beta}_{ct}$ and $\boldsymbol{X}_{ctp}\boldsymbol{\beta}_{ctp}$ have analogous interpretations for trip and point-level variables. $b_{0c} + b_{0ct} + \varepsilon_{ctp}$ is the random part, $b_{0c} \sim N(0, \sigma_c{}^2)$ is the random intercept for cyclist c, capturing the cyclist c-specific deviation from the overall intercept, and $b_{0ct} \sim N(0, \sigma_{ct}{}^2)$ is the random intercept for trip t of cyclist c. ε_{ctp} is the residual error at the point level. It is correlated with the residual at the preceding point, with a serial correlation coefficient ρ ($|\rho| < 1$), which specifies the autoregressive residual structure.

Table 1. Descriptive statistics of observed indicators for FMM ($n = 227$).

Indicators	Mean	Min.	Max.
Std. dev. of temperature	2.789	0.272	7.751
Std. dev. of humidity	10.733	0.726	20.199
Std. dev. of wind speed	1.277	0.325	2.283
Std. dev. of precipitation intensity	0.122	0.000	0.700
Rain length ratio (%)	6.2	0.000	33.6

4. Result

4.1. Descriptive analysis of FMM indicators

Cyclists experienced different temperatures, humidity and wind speed, while some cyclists did not cycle during rain, as shown in the minimal rain length ratio of zero (Table 1).

4.2. The weather-sensitivity classification result

Among four FMM variations, the most restrictive model (allowing only a variant factor mean) and the least restrictive model (allowing all parameters to vary) successfully converged during parameter estimation with either two or three latent classes and one factor. Therefore, the optimal class number was chosen from these four models. In addition, since we only focus on the categorical weather-sensitivity classes, the factor of each latent class, namely the continuous latent variable, is not discussed.

All fit indices, except for LMR, show that the least restrictive FMM with three classes and one factor is the best solution (Table 2). A model with a lower absolute value of LL or a lower AIC, BIC or ABIC is preferred over the one with higher values. Entropy evaluates the extent to which the identified classes differ, with higher entropy values meaning better distinction. All models have acceptable entropy values exceeding 0.8 (Ramaswamy et al., 1993), indicating a good separation. BLRT and LMR compare the current model with the model with one fewer class (Lo, 2001), and a significant p-value confirms the better fit of the current model. For the least restrictive FMM variation, BLRT chooses the three-class solution, while LMR rejects it. Despite this inconsistency, all indices considered, the three-class, one-factor FMM with all parameters varying across classes is the best fitting model. However, it is still recommended to consider the theoretical expectation and the interpretation of classes when deciding the class number (Marsh et al., 2009; Morin & Marsh, 2015; Muthen, 2003). From here, only the two least restrictive FMMs were

Table 2. Fit indices for four converged FMM models.

Model		LL*	AIC	BIC	ABIC	Entropy	BLRT	LMR
FMM with only variant factor mean	Two-class	−361.63	747.26	788.36	750.33	0.803	<0.001	0.036
	Three-class	−324.52	677.05	725.00	680.63	0.828	<0.001	0.240
FMM with all variant parameters	Two-class	−136.01	336.03	445.63	344.21	0.933	<0.001	0.329
	Three-class	−32.50	161.00	325.40	173.27	0.894	<0.001	0.197

*LL: log-likelihood; AIC: Akaike's Information Criterion; CAIC: Consistent AIC; BIC: Bayesian Information Criterion; ABIC: Sample-size Adjusted BIC; BLRT: Bootstrap Likelihood Ratio Test; LMR: Lo-Mendell-Rubin Likelihood Ratio

Table 3. Descriptive statistics of classes.

Model		Two-class model		Three-class model		
Class		Class 1	Class 2	Class 1	Class 2	Class 3
Obs.		50	177	48	158	21
%		22	78	21.1	69.6	9.3
Mean	Std. dev. temperature	2.523	2.862	2.413	2.869	2.980
	Std. dev. humidity	9.891	10.964	9.877	11.010	10.519
	Std. dev. wind speed	1.089	1.329	1.090	1.347	1.171
	Std. dev. precipitation	0.009	0.153	0.006	0.145	0.196
	Rain length ratio	0.006	0.077	0.005	0.064	0.164
Mean trip number				67.3	467.7	66.8
Mean winter trip number				13.3	100.7	23.2
Share of winter trip				19.8%	21.5%	34.7%

considered, as their fit indices are significantly better than those of the restrictive models.

The three-class solution aligns better with expectations compared to the two-class solution. Both models detected a group of people (Class 1) who are very sensitive to weather and a group (Class 2) less influenced by weather conditions (Table 3). The three-class solution also recognized a group of 21 people (Class 3) with the biggest standard deviation of the rain intensity and rain length ratio and other indicators similar to Class 2. It confirms the expectation and literature (Spencer et al., 2013) that some cyclists are less sensitive to precipitation. Therefore, the three-class solution was chosen.

In the chosen solution, namely the three-class, one-factor model, most cyclists (Class 2) are less sensitive to weather, and a minority (Class 1) is highly sensitive to weather. They are regarded as the "less-weather-sensitive" and "weather-sensitive" groups, respectively. Class 3, with only 21 cyclists, is defined as the "less-rain-sensitive" group, whose standard deviation of precipitation intensity and the rain length ratio are much higher than those of the other two groups.

Less-sensitive cyclists generally make more trips and have a higher percentage of winter trips (Table 3). Cyclists in the less-weather-sensitive group made 468 trips on average, while cyclists in the weather-sensitive group made 67 trips. Regarding winter trips, both less-weather-sensitive and less-rain-sensitive groups have a higher number and percentage than the weather-sensitive group.

4.3. Descriptive analysis of multilevel model variables

Table 4 describes all variables included in the multilevel models, distinguishing the cyclist, trip and tracking point levels. It reports the number of observations, the share per category for categorical variables, or the mean for continuous variables. The last column presents the mean tracking point speed for tracking point-level dummy variables and the mean trip speed for trip and cyclist-level dummy variables. The variables "Sunshine duration" and "Wind shelter" range between 0 and 1. Minimum and maximum trip lengths are 0.5 and 85.9 km, respectively. Generally, only a few trips are observed during bad weather conditions. For example, less than 0.5% of trips occur during snow and ice, while 1.4% take place in fog. Rainy conditions account for 6.8% of tracking points, and strong winds cover around 14%. This is likely due to the infrequent bad weather situations compared to good weather and decreased bicycle trip generation in such conditions.

4.4. Multilevel model results

4.4.1. Multilevel structure

Four multilevel models were estimated to understand the influence of weather on cycling speed. The first model (Null model) included only random intercepts at the cyclist and trip levels without predictors. It has two purposes: first, the random intercepts illustrate how much the variation in speed is due to the differences between cyclists and between trips. Also, this model serves as a baseline to check the extent to which the added predictors can explain the speed variation. The second model examined the direct influence of weather indicators and weather-sensitivity groups on cycling speed. Based on it, the third model included the interaction term between weather-sensitivity groups and rain to explore cyclist heterogeneity. Rain rather than other weather components was included in the interaction term because the three weather-sensitivity groups differ in their sensitivity to rain, while "less-weather-sensitive" and "less-rain-sensitive" groups are similarly sensitive to other weather components. Also, the interaction term between wind and shelter was added as an example to explore geographic heterogeneity. Finally, other variables, including time of the trips, bicycle infrastructure, and land use, were controlled in the fourth model (Full model) to reduce possible confounding effects.

The random intercepts of the Null model (Table 5) show that 28.0% ($7.335/(7.335 + 4.247 + 14.599)$) of the speed variance is between cyclists, and 16.2% is between trips. This illustrates inherent speed differences between cyclists and between trips of a cyclist, supporting the estimation of multilevel models. From the Null model to the Full model, the remaining unexplained variance keeps decreasing, and the model fit gradually improves, indicating that the added variables explain additional speed variation. Comparing models 2 and 4 shows that the variance explained by weather conditions is relatively smaller than that explained by bicycle infrastructure and land use. This is probably because people cycle less frequently during bad weather. The autoregressive coefficients (ρ) are significant and similar across the four models, ranging from 0.492 to 0.543. These positive values indicate that estimated residual deviations tend to

Table 4. Descriptive statistics.

Variable	Obs.	Share	Mean (Std. Dev.)	Avg speed
Cyclist level variables	**224**			
Weather-sensitivity group				
Weather-sensitive group	46	20.5%		18.3
Less-weather-sensitive group	157	70.1%		18.6
Less rain-sensitive group	21	9.4%		17.9
Trip level variables	**65,122**			
Temperature				
<10	23,570	36.2%		18.1
10–25	39,189	60.2%		18.3
>25	2,363	3.6%		18.4
Humidity				
<70	29,866	45.9%		18.2
70–90	25,253	38.8%		18.3
>90	10,003	15.3%		18.5
Fog				
Yes	942	1.4%		18.6
No	64,180	98.6%		18.2
Snow				
Yes	293	0.4%		17.2
No	64,829	99.6%		18.3
Thunder				
Yes	773	1.2%		18.4
No	64,349	98.8%		18.3
Ice occurrence				
Yes	103	0.2%		17.3
No	65,019	99.8%		18.3
Sunshine duration			0.4 (0.42)	
Light conditions				
Daylight	56,932	87.4%		18.2
Twilight	5,906	9.1%		18.6
Darkness	2,284	3.5%		18.0
Trip length (km)			5.4 (6.4)	
Peak hours				
Off-peak	42,875	65.8%		18.0
Morning peak	8,273	12.7%		19.3
Evening peak	13,974	21.5%		18.5
Day type				
Weekday	50,202	77.1%		18.3
Weekend	13,497	20.7%		17.8
Holiday	1,423	2.2%		17.9
Point level variables	**5,260,281**			
Precipitation				
No rain	4,902,295	93.2%		19.1
Rain	357,986	6.8%		18.8
Wind				
No wind	526,616	10.0%		19.5
Light tailwind	1,470,593	30.0%		19.7
Light crosswind	988,144	18.8%		19.1
Light headwind	1,518,394	28.9%		18.5
Strong tailwind	269,944	5.1%		19.7
Strong crosswind	192,098	3.7%		18.7
Strong headwind	294,492	5.5%		17.5
Wind shelter	5,260,281		0.07 (0.20)	
Land use				
Built-up	1,933,278	36.8%		17.9
Semi-built-up	102,122	1.9%		18.5
Transport use	406,002	7.7%		18.5
Industry use	367,557	7.0%		19.3
Nature area	2,451,322	46.6%		20.1
Bike lane type				
Pedestrian area	24,187	0.5%		16.2
Residential road	2,016,699	38.3%		19.0
Bike street	564,331	10.7%		19.8
Bike tracks	156,156	3.0%		19.3
Bike path along main road	1,677,737	31.9%		19.2
Solitary bike path	821,171	15.6%		18.5
Intersection type				
Non-intersection	5,101,095	97.0%		19.2
Roundabout	30,154	0.6%		16.4
Intersection without traffic lights	56,819	1.1%		16.0
Intersection with traffic lights	72,213	1.4%		11.4
Intersection adjacent				
Others	5,061,001	96.2%		19.1

(*continued*)

Table 4. Continued.

Variable	Obs.	Share	Mean (Std. Dev.)	Avg speed
Before no light	49,689	0.9%		18.6
Before light	51,621	1.0%		17.3
After no light	47,937	0.9%		17.0
After light	50,033	1.0%		15.8
Turn				
Non-turn	4,476,563	85.1%		19.6
Before right	270,706	5.1%		17.0
Before left	293,976	5.6%		16.8
After right	109,977	2.1%		14.7
After left	109,059	2.1%		14.6
Bridge/tunnel				
Tunnel	61,745	1.2%		19.1
Normal	5,105,038	97.0%		19.1
Bridge	93,498	1.8%		16.9
Slope				
Flat	5,144,425	97.8%		19.1
Downhill	52,233	1.0%		17.9
Uphill	63,623	1.2%		16.2

persist over time within a trip, with around half of the deviation at one point carrying over to the next point.

The effects of most weather variables keep constant, showing model robustness throughout the last three models. The coefficients indicate the change in cycling speed (km/h) due to one unit change in predictors. For example, the coefficient of snow (−0.808) in the second model means that cycling speed is 0.808 km/h lower during snow than in a clear situation.

4.4.2. The effect of weather and weather-sensitivity groups on speed

In this section, if the coefficients of a weather variable are similar in the last three models, the result of the Full model is described. Otherwise, the coefficients of the models are compared.

We split weather factors into three categories, based on the major path through which they are assumed to influence cycling speed, namely safety, effort and comfort. Components mainly related to safety decrease speed substantially. Snow decreases cycling speed by 0.875 km/h, and similarly, the occurrence of ice decreases speed by 0.523 km/h. Twilight and darkness, meaning limited visibility, decrease cycling speed by 0.254 km/h and 0.126 km/h compared to daylight. Unexpectedly, fog, which also reduces visibility, increases speed by 0.175 km/h.

Wind affects the effort needed for cycling, and its effects on cycling speed depend on the wind direction and force. Tailwinds increase cycling speed, and headwinds and crosswinds decrease cycling speed, while the negative effect of headwinds is more pronounced than the positive effect of tailwinds, and the effect of crosswinds is small. Obviously, strong winds have greater effects than light winds. The interaction between wind and shelter in Model 3 and 4 shows that shelter can mitigate the impact of wind. Specifically, while strong headwinds reduce speed by 0.8 km/h, full shelter decreases their negative effect by 0.2 km/h. Moreover, the positive effects of tailwinds are even completely removed by full shelter. Light and strong crosswinds reduce speed minimally, and

Table 5. Model results.

Variables	Models			
	Model 1: null	Model 2: weather indicators only	Model 3: with interaction terms	Model 4: full
Cyclist level variables				
Weather-sensitivity, the weather-sensitive group as ref.				
Less-weather-sensitive group		0.436	0.435	0.449
Less-rain-sensitive group		−0.280	−0.351	−0.216
Trip level variables				
Temperature, 10–25 °C as ref.				
<10		−0.184***	−0.184***	−0.185***
>25		0.046	0.045	0.058
Humidity, 70–90% as ref.				
<70		−0.160***	−0.160***	−0.097***
>90		0.135***	0.135***	0.022
Fog		0.150*	0.150*	0.175**
Thunder		0.020	0.021	0.094
Sunshine duration		0.005***	0.005**	−0.005**
Snow		−0.803***	−0.808***	−0.875***
Ice occurrence		−0.729***	−0.733***	−0.523**
Light conditions, daylight as ref.				
Twilight		−0.106***	−0.106***	−0.254***
Dark		−0.272***	−0.272***	−0.126**
Trip length				0.081***
Peak hours, off peak hour as ref.				
Morning peak hours				0.555***
Evening peak hours				0.182***
Day types, weekdays as ref.				
Weekend				−0.461***
Holiday				−0.625***
Point level variables				
Rain		0.033	−0.224	0.144
Weather-sensitivity * rain				
Less-weather-sensitive group			0.181	−0.107
Less-rain-sensitive group			0.567*	0.165
Wind, no wind as ref.				
Light tailwind		0.194***	0.217***	0.259***
Light crosswind		−0.109***	−0.170***	−0.129***
Light headwind		−0.388***	−0.371***	−0.377***
Strong tailwind		0.346***	0.387***	0.497***
Strong crosswind		−0.212***	−0.265***	−0.208***
Strong headwind		−0.816***	−0.825***	−0.821***
Shelter from wind upstream		−0.669***	−0.672***	−0.690***
Shelter * wind				
Light tailwind			−0.268***	−0.301***
Light crosswind			0.485***	0.402***
Light headwind			−0.201***	−0.111***
Strong tailwind			−0.452***	−0.527***
Strong crosswind			0.428***	0.376***
Strong headwind			0.093*	0.214***
Land-use, built-up area as ref.				
Semi-built-up area				0.285***
Transport use area				−0.122***
Industry use area				0.301***
Nature area				0.576***
Bike lane, residential road as ref.				
Pedestrian areas				−0.531***
Bike street				0.353***
Bike track				0.207***
Bike path along road				0.003
Solitary bike path				−0.137***
Bridge/tunnel, non-bridge/tunnel as ref.				
Tunnel				0.204***
Bridge				−1.433***
Intersection, non-intersection as ref.				
Roundabout				−1.791***
Inter. without traffic lights				−2.404***
Inter. with traffic lights				−6.691***
Before/after intersection, others as ref.				
Before Inter. without traffic lights				−0.351***
Before Inter. with traffic lights				−2.026***
After Inter. without traffic lights				−1.431***
After Inter. with traffic lights				−2.763***
Before/after turn, others as ref.				
Before right turn				−1.131***

(*continued*)

Table 5. Continued.

Variables	Models			
	Model 1: null	Model 2: weather indicators only	Model 3: with interaction terms	Model 4: full
Before left turn				−1.218***
After right turn				−3.109***
After left turn				−3.079***
Slope, flat road as ref.				
Downhill				−0.390***
Uphill				−1.857***
Constants	18.386***	18.406***	18.409***	18.261***
Random intercept				
Cyclist variance	7.335***	7.219***	7.234***	6.180***
Trip variance	4.247***	4.050***	4.049***	3.861***
Tracking point residual variance	14.599***	14.425***	14.419***	12.133***
ρ	0.543***	0.537***	0.537***	0.492***
Model fit				
LL	−13677581	−13669654	−13668843	−13382817

full shelter reverses their effects, increasing speed by around 0.3 $(-0.129 + 0.402)$ and 0.2 $(-0.208 + 0.376)$ km/h, respectively. An exception is light headwinds, whose negative influence expands by 0.1 km/h with full shelter.

The comfort level of cyclists is related to temperature, humidity and rain. Cold weather ($< 10^\circ$C) reduces cycling speed, while moist air increases cycling speed, but their effects are minimal. Rain, however, is not found to significantly influence cycling speed.

Unexpectedly, different weather-sensitivity groups do not differ significantly in cycling speed. In addition, the influence of rain is largely consistent across groups. The only exception is the interaction between rain and the less-rain-sensitivity group in Model 3, which shows a positive effect.

4.4.3. The effect of other factors

All controlled bicycle infrastructure and land use variables significantly influence cycling speed. Among them, intersections and turns have the biggest effects; cycling is substantially slower at intersections with traffic lights and slightly slower at intersections without traffic lights and roundabouts than at normal roads. The roads close to intersections and turns also decrease cycling speed strongly. Roads involving elevation changes affect cycling speed; cycling uphill is much slower, and cycling downhill is slightly slower than flat roads. Bridges reduce speed, but tunnels increase speed. The effect of bike lane types and land use is relatively small, but considering their constant existence along the route, their influence cannot be ignored. Among all bike lane types, cycling on bicycle streets is the fastest, followed by bicycle tracks. Bike paths along main roads do not differ from residential roads. Solitary bike paths and especially pedestrian areas decrease speed. Regarding land use types, natural areas have the highest speed, followed by semi-built-up areas and industrial use areas, while transport use areas decrease cycling speed compared to the built-up area.

Two time-related variables and the trip length also influence cycling speed. Cycling during holidays and weekends is slower than during weekdays. Rush hours, especially the morning rush hour, increase speed. The trip length minimally increases speed.

5. Conclusion and discussion

5.1. Discussion

This study investigates the influence of weather on cycling speed, considering the existence of weather-sensitivity groups, cyclist heterogeneity and geographic heterogeneity.

5.1.1. Weather-sensitivity groups

Three weather-sensitivity groups among participants are distinguished using a factor mixture model. A “weather-sensitive” group accounts for 20.5% of the respondents, and most respondents (70.1%) are less affected by weather (“less-weather-sensitive”). This corresponds to other studies: Hudde (2023) observed only a 2.5% gap in bicycle modal share between summer and winter in the Netherlands, and Thomas et al. (2013) found hardly any seasonal variations in utilitarian cycling volumes. A “less-rain-sensitive” group, which is even less affected by rain, accounts for only 9.4%. This also aligns with earlier studies that, despite low weather-sensitivity, rain discourages cycling in the Netherlands (Böcker & Thorsson, 2014; De Kruijf et al., 2021; Helbich et al., 2014). Obviously, less weather-sensitive cyclists made more trips than sensitive cyclists. This confirms studies that found that frequent and experienced cyclists are more likely than others to cycle in bad weather (Faber et al., 2022; Motoaki & Daziano, 2015).

Cycling speed is often considered to reflect cyclists’ physical capacity, as indicated by speed differences between age groups and genders (e.g. Romanillos & Gutiérrez, 2020). However, we do not observe significant speed differences between weather-sensitivity groups, suggesting that weather-sensitivity may not be associated with physical capacity but with mindset and attitude. Consistent with this interpretation, the influence of rain on cycling speed is largely similar across sensitivity groups. The only exception is that the speed gap between less-rain-sensitive and rain-sensitive cyclists is 0.5 km/h larger during rain than in dry conditions. After controlling for infrastructure and land-use covariates, this effect becomes insignificant, suggesting that rain-related speed differences partly reflect rain-specific route choices or systematic environmental differences between groups.

5.1.2. Weather conditions

Weather influences cycling speed through three aspects: safety concerns, required physical effort and comfort level. While each weather component can affect multiple aspects, it is assumed that one of these aspects plays a dominant role; for example, snow influences safety, effort and comfort simultaneously, but safety is usually the primary concern.

Safety concerns regarding snow and ice significantly decrease cycling speed. Likely because of the risk of slipping or skidding, cyclists tend to slow down for better control over their bicycle. Similar findings were reported by Shoman et al. (2023). Note that the current models may underestimate the full impact of untreated snowy and icy conditions. In the Netherlands, municipalities usually take preventive measures, such as gritting with salt or brine solutions, before expected snowfall or icy roads (Wilson, 2021). However, this maintenance is not uniformly applied across all streets; main cycling routes are prioritized (BicycleDutch, 2013), while small residential streets may not be gritted (Gemeente Amsterdam, 2025). In addition, snow accumulation along the edges of bicycle paths after cleaning can reduce the effective riding width (BicycleDutch, 2021). Therefore, the estimated coefficients likely reflect the influence of partially cleared snowy and icy conditions rather than fully untreated surfaces.

In addition, people who persist in cycling during snow and ice may make additional effort to compensate for their influence, such as more corrective steering movements (Bärwolff et al., 2022) and more concerns about falling (Shoman et al., 2023). This indicates that snow and ice not only decrease cycling speed but also require extra effort and cause safety concerns.

Twilight and darkness decrease cycling speed to a lesser extent, similar to Yan et al. (2025): reduced visibility shortens the reaction distance to risky situations, causing slow riding. Remarkably, fog positively influences cycling speed (see also Fietstelweek, 2017). A possible explanation may be the lower bicycle volume during fog, which is around half of the volume during clear weather in our dataset. The positive effects of lower bicycle volumes exceed the negative effects of low visibility, causing a relatively high cycling speed.

Wind alters the resistance experienced, thus influencing the required physical effort and speed. Nearby upwind buildings block wind and provide shelter, reducing the positive influence of tailwinds and mitigating the negative impact of crosswinds and strong headwinds. Such a mitigation effect is not observed for light headwinds, possibly due to the complex wind environment around buildings (Mittal et al., 2018). Nevertheless, this exception does not overturn the overall evidence that wind shelter moderates the impact of wind conditions on cycling speed. Similar but less detailed results were found in studies where bicycle volumes (Ahmed et al., 2010) and bicycle trip generation (Helbich et al., 2014) were more strongly influenced by wind in remote areas than in urban areas.

Temperature is related to the comfort level, influencing cyclists' physical performance and cycling speed. A low temperature makes muscles stiff and inflexible. In addition, cyclists may wear multiple layers in cold conditions, restricting their movements and decreasing cycling speed. The negative influence of low temperature was also found by Strauss and Miranda-Moreno (2017) and Eriksson et al. (2019). However, the positive effect of temperature becomes insignificant when it reaches 25 °C, probably due to the increased respiratory effort to dissipate heat. This is similar to studies finding that high temperatures discourage the choice of cycling (De Kruijf et al., 2021).

Rain influences cycling speed in several ways. On the one hand, cyclists may increase their speed to reduce their exposure to discomfort caused by rain. On the other hand, rain likely raises safety concerns, such as slippery roads, and requires additional effort, due to wearing raincoats, both of which can reduce speed. Moreover, self-selection occurs here: people who keep cycling in the rain are often fitter and more experienced; they achieve a higher average speed than the larger group that cycles in dry conditions (which includes both experienced and inexperienced cyclists). Most previous studies have found an overall positive effect of rain on cycling speed (Fietstelweek, 2017; Maurer et al., 2025; Yan et al., 2025). However, the current study does not find a significant positive effect of rain. One possible reason is that the cycling data in this study cover all seasons, and cyclists' reactions to rain may vary across seasons due to temperature differences and thermal comfort. For example, rain during colder seasons may create stronger discomfort and thus encourage cyclists to speed up, whereas rain during warmer periods may lead to weaker behavioral adjustments. Previous studies, such as Yan et al. (2025), which collected data during winter, and Fietstelweek (2017), which used cycling data from a single week in September, may reflect more season-specific behavioral responses.

In this study, the estimated coefficients of weather conditions are relatively small compared to those of some bicycle infrastructure factors, such as intersections and turns. However, their actual influences on cycling speed are likely underestimated because cyclists may actively compensate for these influences by adjusting their mental and physical effort and sacrificing comfort. For example, cyclists lean forward and pedal harder during headwinds while they exert less effort with tailwinds. As Pérez Castro et al. (2025) found, cyclists hardly change their speeds for light winds, although wind changes resistance during cycling.

Furthermore, interpreting the influence of weather components on overall trip speed using the model coefficients is not straightforward. Each coefficient reflects the speed change at a single observation (i.e. a GPS tracking point) due to a one-unit change in the corresponding independent variable. However, it does not directly capture the overall influence of a variable on trip-level speed changes. This overall effect depends partially on the duration or frequency of exposure to that variable. For example, the influence of weather can persist throughout the entire trip, while certain infrastructure features, such as intersections and turns, are only passed occasionally at specific locations within a trip. Therefore, the coefficients of weather components may underestimate their cumulative effect over a full trip.

5.2. Policy implications

By mitigating the negative effects of bad weather on cycling speed, the issues related to safety, effort and comfort experienced by cyclists are partially alleviated, and an acceptable travel time could be achieved. As a result, the competitiveness of cycling compared to other motorized modes can be improved. The focus should be on snow, ice, darkness and wind, which have relatively strong effects. There are two types of solutions to this.

One type is bicycle infrastructure construction and maintenance. First and foremost, keeping bicycle facilities clear is essential, e.g. by promptly clearing leaves, snow and ice from bicycle infrastructure. For places with a cold and long winter, an underground road heating system (Yoshitake et al., 2011) or an ice-resistant road surface (Chen et al., 2018) can clear snow and ice automatically and efficiently. Automatic street lighting (which is becoming cheaper due to LED lights), especially in areas with complex and busy traffic situations, makes cycling easier and safer in dark situations. For roads that are exposed to wind, or even suffer from wind tunnel effects, trees and other vegetation are a good option to reduce wind speed (Hefny Salim et al., 2015), especially as cities need to green up anyway to become more climate-adaptive (Schwaab et al., 2021).

Another solution is a cycling navigation system which can provide cyclists with suitable route recommendations based on real-time weather. It accounts for the fact that cyclists may not have all the information to make the best use of infrastructure, although some can mitigate the negative effects of specific weather conditions. The system relies on (1) precise weather forecasts, (2) comprehensive information about the existing infrastructure and (3) knowledge about the interrelationship between cycling speed, weather and infrastructure. The recommended routes should consider route distance and the shelter effect of route attributes for real-time weather conditions, such as rain or wind. It is also recommended to provide route suggestions tailored to user preferences. Such a navigation system is an especially good addition if weather-proof cycling facilities are provided.

Weather-sensitivity groups vary in the weather conditions under which they cycle, but their speeds do not vary significantly. This suggests that the mindset of travelers, rather than their physical conditions, decides the acceptance of cycling in bad weather. It also illustrates the possibility for most people to cycle year-round, at least in places with a similar climate to that of the Netherlands. Winter weather conditions discourage cycling most, and therefore, local governments could invest in winter cycling campaigns to boost the idea that cycling is feasible in winter, especially for weather-sensitive travelers. Employers can also provide their employees with equipment, such as raincoats, to support cycling.

5.3. Future research

Building on the current study, future research can further enhance our understanding of how weather influences cycling speed.

The present study is based on a unique, comprehensive and highly detailed database of bicycle use. However, what could be added to future data collections are characteristics of cyclists, including socio-demographics, cycling-related equipment, physical condition, cycling-related attitudes and mindset, and characteristics of the bicycle, such as type and condition.

It is also recommended to explore the mechanisms through which weather influences cycling speed. The current paper assumes safety concerns, physical effort needed, and comfort levels, but these have not been examined. Qualitative research could be conducted to investigate cyclists' perceptions of different weather components and how these influence their speed decisions.

Cycling route choice strategies under different weather conditions could be explored. We found that the influence of some weather components, such as the interaction effect between rain and weather sensitivity groups, changed after including land use and bicycle infrastructure variables, demonstrating possible correlations between route choice and weather conditions. It is possible that some route features can act as shelters for specific weather conditions, and routes are therefore chosen by cyclists.

We also recommend examining the environmental moderation effects on other weather components, such as rain and temperature. Trees and buildings can reduce the volume and intensity of rain reaching the ground (Alivio et al., 2023), while natural environments along cycling routes can influence cyclists' perceived thermal comfort (Young et al., 2022). In addition, these mitigation effects are likely to vary across seasons, as rain and temperature are perceived differently in winter and summer. This topic relates to cyclists' comfort levels and may influence individuals' mode choice under certain weather conditions.

To conclude, weather significantly impacts cycling speed, potentially reducing the competitiveness of cycling as a mode of transport. This influence tends to increase with climate change. Although weather conditions cannot be changed to suit cyclists' preferences, better design and management of bicycle infrastructure can help mitigate the negative effects of weather. Measures including promptly clearing snow and ice, ensuring sufficient streetlights, and providing shelters in the predominant wind direction, can enhance cyclists' safety and comfort, so that cyclists can maintain their speed in a comfortable and safe way under bad weather conditions.

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