Cycling Speed: Variation and Stability within Rides

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I unwrapped a chocolate called 'PhD research', almost finished it, and tasted a flavour I had never expected. My desire for this chocolate probably dates to my childhood, when I wanted to become a scientist. Although I knew little about scientists or doctors, I regarded them as something sacred and immersed myself in an imagined scientific life. This dream faded for a while but was rekindled when I went to college and saw the 'real' scientific life. I admit that it was not reality, but my own perception. This imagination partly motivated me to come to Delft University of Technology. It is fascinating to conduct cycling-related research in a cycling-friendly country, especially because I like cycling. Everyone on the streets is part of my observation, and each ride deepens my understanding of cycling. Perhaps because of my current research, I can't stop recalling my cycling-related projects during my bachelor's and master's studies, as if a mysterious force has led me here. Cycling is easy for me, but understanding cycling behaviour is not, which is reflected in my long PhD journey. However, I am truly grateful for this challenging journey, which has allowed me to taste the tempting chocolate I once imagined as a child.

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Hong Yan

Delft, March 2026

Content

Summary

Cycling speed influences the attractiveness of cycling compared to other transport modes. Theoretically, a relatively high and stable cycling speed increases cycling accessibility by reducing travel time for a given route and increasing the number of opportunities to reach different locations within a given time. Empirically, the sales and use of electric bicycles continue to grow, illustrating cyclists' preference for fast and smooth cycling. In addition, new bicycle infrastructure, such as bicycle highways, supports cyclists' demands for faster cycling. Owing to the importance of cycling speed, a growing body of research has examined its determinants, mainly focusing on aggregated speeds at specific locations and average speeds of trips or road segments.

However, cycling speed not only varies between specific locations and between cyclists but also changes almost constantly during a ride. This change is mainly caused by factors that vary along the route, such as bicycle infrastructure, land use, and apparent wind, but also depends on the characteristics of cyclists and bicycles. Exploring this change and its determinants can reveal the route attributes that support or prevent smooth cycling. This knowledge is important for urban and transportation planning to facilitate smooth cycling and make cycling more attractive. The speed changes within a ride can be considered from two perspectives: where speed is high or low (speed variation) and how speed changes over the course of a ride (speed stability). Yet, individual speed variation and stability within a ride remain largely unexamined.

Therefore, this thesis aims to explore speed variation and stability within a ride, as well as their determinants. Before conducting the empirical research, existing studies on cycling speed are reviewed for two purposes. First, a conceptual model is developed to describe the mechanism through which various determinants influence the speed of a trip, and a research agenda based on this model is proposed for comprehensively exploring cycling speed (Chapter 2). Second, the advantages and disadvantages of study designs employed in investigating the determinants of cycling speed are discussed (Chapter 3). These two literature review chapters help identify specific empirical research questions, select influential factors and relationships that should be considered, and choose appropriate research methods to address the research questions.

Conceptual model (Chapter 2)

The developed conceptual model assumes that cycling speed is embedded in a feedback loop. Individual characteristics and context influence cycling speed directly and indirectly through trip choices, such as route choice and bicycle type choice. Speed inherently affects an individual's accessibility, safety, health, and well-being. These effects can alter one's characteristics either immediately during a trip, such as in the case of severe traffic accidents, or gradually through daily cycling, which improves physical condition and fosters positive attitudes related to cycling. Complicated relationships exist among these factors, such as moderation effects and self-selection. Ignoring these effects may lead to biased results. For example, individuals who prefer higher riding speeds may choose a residence or route that allows faster cycling; failing to account for this can wrongly attribute the effect of individual preferences to the built environment.

Empirical study designs (Chapter 3)

Based on empirical study designs employed in examining the determinants of cycling speed, existing research can be classified into targeted-segment-based studies, experiment-based studies, and whole-trip-based studies. Targeted-segment-based studies focus on speed at targeted road segments and examine specific route attributes, such as bike lane types. As a result, they capture only limited portions of trip speed information and offer relatively narrow insights. Experiment-based studies primarily observe and examine within-trip behaviour, such as phone use and cyclists' interactions with other road users, which are less likely to be observed by the other two approaches. Additionally, they can explore the mechanisms behind certain influences through experimental design. Whole-trip-based studies utilise speed data from entire trips, which include complete speed information and can reveal speed variation within a ride. In addition, these studies can simultaneously examine the influence of the characteristics of cyclists, bicycles, trips, and contexts. However, their speed calculation and analysis methods are complicated. Earlier studies typically relied on data from targeted trip segments, whereas more recent research increasingly employs full-trip data.

Following the literature review, this thesis focuses on three research topics that have received limited attention. The first topic is speed variation within a ride and the simultaneous influence of the characteristics of cyclists, bicycles, and contexts. The second topic is the influence of factors that vary over time, such as weather conditions, on speed variation. The third direction focuses on speed stability within a ride, including its definition, recognition and determinants.

To achieve these purposes, this thesis employs a whole-trip-based approach, using data from cycling trips tracked with GPS devices and employing quantitative research methods. GPS devices register a tracking point with the position and time stamp of cyclists every few seconds. Speeds at each tracking point, speed variation, and stability within a ride can, therefore, be calculated. Then, the detailed route characteristics and weather conditions are linked to tracking points based on their geographic locations, and the characteristics of cyclists, bicycles, and trips are connected to the trips. Since the datasets have a hierarchical structure where each cyclist makes several trips, and each trip consists of multiple tracking points, multilevel models are estimated to account for the dependence of observations within a group.

Speed variation within a ride (Chapter 4)

Cycling speed varies significantly within a ride. Within-ride variation (mainly caused by determinants varying during the ride, such as bicycle infrastructure) accounts for approximately half of the total speed variance, followed by between-ride and between-cyclist variations. Cyclists who prefer high speeds tend to ride faster. Trips made on sporty and electric bicycles, and those taken during rush hours, often have a higher speed. Intersections, turns, and both positive and negative slopes decrease cycling speeds. Surprisingly, cycling on physically separated bike lanes is slower than on bicycle streets and bicycle tracks. The influence of bicycle infrastructure on cycling speed varies among cyclists. Cyclists with higher speeds tend

to decelerate more at locations involving regulatory issues and safety concerns, such as intersections and turns.

Weather's influence on cycling speed variation (Chapter 5)

In addition to examining the direct influence of weather conditions on cycling speeds, this chapter considers cyclist and geographic heterogeneity. Cyclists have different levels of tolerance for the weather conditions under which they choose to cycle, and their speeds tend to be influenced differently by the weather. To examine this, different weather sensitivity groups are identified in the samples. Similarly, objects on the ground alter microclimate conditions, causing cycling speeds to be influenced by weather differently across places. This chapter focuses on the wind shelter caused by buildings, which is calculated based on the position of cyclists, their movement directions, wind directions, and the height of surrounding buildings. The interaction terms between weather sensitivity groups and rain, as well as between wind shelter values and wind, are included in regression models to examine heterogeneity.

Weather conditions influence cycling speed through safety concerns, the physical effort required, and comfort. Weather conditions that pose safety concerns, including the presence of snow and ice, significantly decrease cycling speed. Headwinds and crosswinds require extra physical effort during cycling, decreasing cycling speed, while tailwinds increase speed. Stronger winds have a greater influence on speed than light winds. Temperature and humidity affect physical comfort, with warm and humid weather conditions slightly increasing speed. Rain also makes cyclists uncomfortable, and this influence accumulates over time; therefore, cyclists tend to ride faster during rain to reduce their exposure.

We do not find heterogeneity among cyclists regarding the weather's influence on cycling speed, but geographic heterogeneity exists. There are three weather-sensitivity groups: a weather-sensitive group (20.5% of the sample), a less-weather-sensitive group (70.1%), and a less-rain-sensitive group (9.4%), which is similar to the less-weather-sensitive group but even less sensitive to rain. Their speeds do not differ significantly, and they are influenced by rain to a similar extent. Wind shelter moderates the influence of wind on cycling speeds, partially preventing cyclists from being affected by headwinds and crosswinds, and reducing the positive effects of tailwinds.

Cycling speed stability (Chapter 6)

A combination of change point detection and a rule-based algorithm identifies one stable pattern and five unstable speed patterns: increase, decrease, V-shape (deceleration followed by acceleration), reverse V-shape (acceleration followed by deceleration), and complicated patterns that have irregular speed variations. Stable patterns account for around half of the total trip distance and time, while the V-shape pattern is the most frequent unstable pattern. Compared to unstable patterns, stable patterns exhibit a higher speed and lower speed standard deviation. This illustrates that maintaining stable cycling speeds can enhance the attractiveness of cycling, but smooth cycling is often interrupted.

Intersections and turns strongly destabilise cycling speed, often resulting in V-shaped patterns. Decrease patterns occur more frequently before intersections and turns, and increase patterns are more common after them. Cycling on roads with slopes, such as those through tunnels and bridges, exhibits more unstable patterns. Bicycle streets and bicycle tracks provide better speed stability than physically separated bike lanes. Cyclists show heterogeneity in speed stability; those with high speeds tend to have more unstable patterns.

Conclusions

By quantitatively examining cycling speed variation and stability within a ride, this thesis contributes to the literature on the microscopic level of cycling behaviour. The findings highlight that cycling speed is often decreased or destabilised by specific bicycle infrastructure and situations, such as intersections and busy roads. Furthermore, faster trips are influenced more, which means that cyclists cannot fully utilise their physical abilities or benefit from their faster bicycles.

Based on these results, this thesis recommends installing intelligent traffic light systems at intersections where cyclists experience significant speed losses. In addition, providing more space for cyclists at intensively used road segments, such as those along main roads, can reduce the possibility and negative effects of interactions between cyclists, enabling relatively fast and stable speeds.

Furthermore, this thesis recommends an inclusive bicycle system that allows cyclists and other micromobility users to ride at their preferred pace without being influenced by others. This is important as faster cyclists are delayed more by the current bicycle network. It is also relevant for safety, as interactions between road users travelling at different speeds can pose risks, particularly for vulnerable users. To achieve such an inclusive bicycle network, adequate space is necessary to accommodate different micromobility users, for example, through wide bike lanes and bicycle highways. Additionally, regulations, such as maintaining a left lane position during overtaking and implementing speed limits on narrow roads, are essential for protecting vulnerable road users.

Samenvatting

De fietssnelheid beïnvloedt de aantrekkelijkheid van fietsen ten opzichte van andere vervoerswijzen. In theorie verhoogt een relatief hoge en stabiele fietssnelheid de fietsbereikbaarheid doordat de reistijd op een gegeven route afneemt en het aantal mogelijkheden om binnen een bepaalde tijd verschillende bestemmingen te bereiken toeneemt. De verkoopcijfers en het gebruik van elektrische fietsen blijft groeien, wat de voorkeur van fietsers voor snel en soepel fietsen illustreert. Daarnaast ondersteunt nieuwe fietsinfrastructuur, zoals snelfietsroutes, de vraag van fietsers naar hogere snelheden. Vanwege het belang van fietssnelheid richt een groeiende hoeveelheid onderzoek zich op de determinanten, met name op specifieke locaties en op gemiddelde snelheden van ritten of wegsegmenten.

Fietssnelheid varieert echter niet alleen tussen locaties en tussen fietsers, maar verandert ook vrijwel voortdurend tijdens een rit. Deze veranderingen worden vooral veroorzaakt door factoren die langs de route variëren, zoals fietsinfrastructuur, de gebouwde omgeving en waarneembare wind, maar zijn ook afhankelijk van de kenmerken van fietsers en fietsen. Het onderzoeken van deze veranderingen en de achterliggende determinanten kan inzicht geven in de routekenmerken die een soepele fietservaring ondersteunen of juist belemmeren. Deze kennis is van groot belang voor de ruimtelijke ordening en het verkeers- en vervoersbeleid om stabiel fietsen te faciliteren en fietsen aantrekkelijker te maken. De snelheidsveranderingen binnen een rit kunnen vanuit twee perspectieven worden bekeken: waar de snelheid hoog of laag is (snelheidsvariatie) en hoe de snelheid zich in de loop van de rit ontwikkelt (snelheidsstabiliteit). Tot nu toe zijn individuele variatie en stabiliteit van snelheid binnen één rit grotendeels onderbelicht gebleven.

Daarom beoogt dit proefschrift om snelheidsvariatie en snelheidsstabiliteit binnen de rit te onderzoeken, alsmede de achterliggende determinanten. Voorafgaand aan het empirische onderzoek wordt om twee redenen een literatuuronderzoek uitgevoerd naar bestaande studies over fietssnelheid. Ten eerste wordt een conceptueel model ontwikkeld om het mechanisme te beschrijven over de verschillende determinanten die de snelheid van een rit beïnvloeden; op basis daarvan wordt een onderzoeksagenda voorgesteld om fietssnelheid integraal te verkennen (Hoofdstuk 2). Ten tweede worden de voor- en nadelen besproken van onderzoeksbenaderingen die zijn gebruikt om de determinanten van fietssnelheid te onderzoeken (Hoofdstuk 3). Deze twee literatuurhoofdstukken helpen om specifieke empirische onderzoeksvragen te formuleren, relevante factoren en relaties te selecteren, en passende methoden te kiezen om de onderzoeksvragen te beantwoorden.

Conceptueel model (Hoofdstuk 2)

Het ontwikkelde conceptuele model gaat ervan uit dat fietssnelheid is ingebed in een feedback loop. Individuele kenmerken en context beïnvloeden de fietssnelheid direct en indirect via verplaatsingskeuzes, zoals routekeuze en keuze van het type fiets. Snelheid beïnvloed iemands bereikbaarheid, veiligheid, gezondheid en welzijn. Deze effecten kunnen onmiddellijk van invloed zijn tijdens een rit (bijvoorbeeld bij ernstige verkeersongevallen) of geleidelijk via dagelijks fietsen, wat immers de fysieke conditie verbetert en positieve attitudes ten opzichte van fietsen bevordert. Tussen deze factoren bestaan complexe relaties, zoals interactie-effecten en zelfselectie. Het negeren hiervan kan tot vertekende resultaten leiden. Personen die hogere snelheden prefereren, kunnen een woonlocatie of route kiezen die sneller fietsen mogelijk maakt; als dit niet wordt meegenomen, kan ten onrechte een effect van individuele voorkeuren aan de gebouwde omgeving worden toegeschreven.

Onderzoeksbenaderingen (Hoofdstuk 3)

Op basis van de onderzoeksbenaderingen die zijn toegepast om de determinanten van fietssnelheid te bestuderen, kan bestaand onderzoek worden geclassificeerd in bestudering van de rit per segment, experimenten, en studies die de volledige rit bestuderen. Segmentgerichte studies richten zich op de snelheid op specifieke wegvakken en onderzoeken gerichte route-eigenschappen, zoals typen fietspaden. Hierdoor leggen ze slechts een beperkt deel van de snelheidsinformatie van ritten vast en leveren ze relatief beperkte inzichten op. Experimentgerichte studies observeren en analyseren vooral het gedrag binnen een rit, zoals telefoongebruik en de interacties met andere weggebruikers; deze aspecten zijn met de andere twee benaderingen lastiger te observeren. Daarnaast kunnen zij via experimenteel ontwerp mechanismen achter bepaalde invloeden blootleggen. In onderzoek naar de volledige rit, is volledige snelheidsinformatie beschikbaar. In deze studies kan gelijktijdig de invloed van kenmerken van fietsers, fietsen, ritten en contexten worden onderzocht. De berekening en analyse van snelheden is daarbij echter complexer. Eerdere studies vertrouwden vaak op gegevens van geselecteerde segmenten, terwijl recent onderzoek in toenemende mate volledige ritgegevens inzet.

Na de literatuurstudie volgen drie onderzoeksthema’s die tot dusver beperkt aandacht hebben kregen. Het eerste thema is snelheidsvariatie binnen een rit en de invloed van kenmerken van fietsers, fietsen en context. Het tweede thema betreft de invloed van tijdsvariërende factoren, zoals weersomstandigheden, op snelheidsvariatie. Het derde thema richt zich op snelheidsstabiliteit binnen een rit, inclusief de definitie, herkenning en determinanten daarvan.

Om deze doelen te bereiken, wordt de volledige rit bestudeerd, met data van fietsritten die zijn vastgelegd met GPS-apparatuur; kwantitatieve onderzoeksmethoden worden toegepast. GPS-devices leggen om de paar seconden een trackpunt vast met de ruimtelijke positie en het tijdsstempel van de fietser. Op basis hiervan kunnen de snelheid per trackpunt, de snelheidsvariatie en de snelheidsstabiliteit binnen de rit worden berekend. Vervolgens worden gedetailleerde routekenmerken en weersomstandigheden aan de trackpunten gekoppeld op basis van hun geografische locatie, en worden kenmerken van fietsers, fietsen en ritten aan de ritten verbonden. Omdat de datasets een hiërarchische structuur hebben, waarbij elke fietser meerdere ritten maakt en elke rit uit meerdere trackpunten bestaat, worden multilevelmodellen geschat om rekening te houden met de afhankelijkheid van observaties binnen groepen.

Snelheidsvariatie binnen een rit (Hoofdstuk 4)

Fietssnelheid varieert substantieel binnen een rit. Variatie binnen de rit (voornamelijk veroorzaakt door factoren die tijdens de rit veranderen, zoals infrastructuur) verklaart ongeveer de helft van de totale snelheidsvariantie, gevolgd door variatie tussen ritten en tussen fietsers. Fietsers die hoge snelheden prefereren, rijden gemiddeld sneller. Ritten op sportieve en elektrische fietsen, en ritten tijdens de spits, kennen vaak hogere snelheden. Kruispunten, bochten en hellingen omhoog en omlaag, verlagen de snelheid. Opvallend is dat fietsen op fysiek gescheiden fietspaden langzamer is dan op fietsstraten en vrijliggende fietspaden/fietsroutes. De invloed van infrastructuur op snelheid verschilt tussen fietsers: snellere fietsers remmen sterker af op locaties met regels en veiligheidsrisico's, zoals kruispunten en bochten.

Invloed van weer op snelheidsvariatie (Hoofdstuk 5)

Naast de directe invloed van weersomstandigheden op fietssnelheden, wordt in dit hoofdstuk rekening de heterogeniteit tussen fietsers en geografische heterogeniteit bestudeerd. Fietsers hebben verschillende tolerantieniveaus voor de weersomstandigheden waaronder ze ervoor kiezen te fietsen, en hun snelheid naar verwachting op verschillende manieren door het weer worden beïnvloed. Om dit te onderzoeken, worden in de steekproef verschillende weergevoeligheidsgroepen onderscheiden. Ook objecten op maaiveldniveau veranderen het microklimaat, waardoor het weer de snelheid per locatie anders beïnvloedt. De afscherming van de wind (windshelter) door bebouwing, wordt berekend op basis van de positie en bewegingsrichting van de fietser, de windrichting en de hoogte van omliggende gebouwen. Interactietermen tussen weergevoeligheidsgroepen en regen, en tussen windshelterwaarden en wind, worden in de regressiemodellen opgenomen om heterogeniteit te toetsen.

Weersomstandigheden beïnvloeden fietssnelheid via veiligheid, fysieke inspanning en comfort. Weer dat veiligheidsrisico's geeft—zoals sneeuw en ijs—verlaagt de snelheid significant. Tegenwind en zijwind vragen extra inspanning en drukken de snelheid, terwijl meewind de snelheid verhoogt. Sterkere wind heeft een groter effect dan zwakke wind. Temperatuur en luchtvochtigheid beïnvloeden het fysieke comfort; warm en vochtig weer verhogen de snelheid licht. Regen is bovendien oncomfortabel en dit effect stapelt zich op in de tijd; daarom rijden fietsers tijdens regen vaak sneller om hun blootstelling te verkorten.

Er zijn geen aanwijzingen voor heterogeniteit tussen fietsers in de wijze waarop het weer de snelheid beïnvloedt, maar geografische heterogeniteit blijkt wel aanwezig. Drie weergevoeligheidsgroepen worden onderscheiden: een weersgevoelige groep (20,5%), een beperkt-weersgevoelige groep (70,1%) en een beperkt-regengevoelige groep (9,4%); deze laatste lijkt op de beperkt-weersgevoelige groep, maar is nog minder gevoelig is voor regen. Hun snelheden verschillen niet significant en de invloed van regen is vergelijkbaar. Windshelter dempt de invloed van wind op fietssnelheden: het beschermt deels tegen tegen- en zijwind, en het vermindert de positieve effecten van meewind.

Snelheidsstabiliteit (Hoofdstuk 6)

Met een combinatie van change-pointdetectie en een rule based algoritme wordt één stabiel patroon en vijf onstabiele patronen onderscheiden: toename, afname, V-vorm (vertraging gevolgd door versnelling), omgekeerde V-vorm (versnelling gevolgd door vertraging) en complexe patronen met onregelmatige snelheidsfluctuaties. Stabiele patronen beslaan ongeveer de helft van de totale ritafstand en ritduur; het V-vormpatroon is het meest voorkomende onstabiele patroon. In vergelijking met onstabiele patronen vertonen stabiele patronen een hogere gemiddelde snelheid en een lagere snelheidsstandaarddeviatie. Dit laat zien dat het handhaven van stabiele snelheden de aantrekkelijkheid van fietsen kan vergroten, maar dat vloeiend fietsen vaak wordt onderbroken.

Kruispunten en bochten destabiliseren de snelheid sterk en leiden vaak tot V-vormpatronen. Patronen van afname blijken vaker voor te komen vóór kruispunten en bochten, terwijl patronen van toename juist vaker ná dergelijke punten voorkomen. Fietsen op wegen met hellingen, zoals in tunnels en over bruggen, kent meer onstabiele patronen. Fietsstraten en vrijliggende fietsroutes bieden betere snelheidsstabiliteit dan fysiek gescheiden fietspaden. Er is heterogeniteit tussen fietsers: wie gemiddeld sneller rijdt, vertoont meer onstabiele patronen.

Conclusies

Door de snelheidsvariatie en snelheidsstabiliteit binnen een rit kwantitatief te bestuderen, draagt dit proefschrift bij aan de literatuur over het microniveau van fietsersgedrag. De bevindingen benadrukken dat de fietssnelheid vaak wordt verlaagd of gedestabiliseerd door specifieke elementen in de infrastructuur en door situaties zoals kruispunten en drukke wegen. Bovendien worden snellere ritten sterker beïnvloed, wat betekent dat fietsers hun fysieke capaciteiten en de voordelen van sneller fietsen niet volledig kunnen benutten.

Op basis van deze resultaten wordt aanbevolen om intelligente verkeerslichtsystemen te installeren op kruispunten waar fietsers aanzienlijke snelheidsafnames ervaren. Daarnaast kan het bieden van meer ruimte voor fietsers op intensief gebruikte wegvakken, bijvoorbeeld langs hoofdwegen, de kans en negatieve effecten van interacties tussen fietsers verminderen, waardoor relatief hoge en stabiele snelheden mogelijk worden.

Verder pleit dit proefschrift voor een inclusief fietssysteem waarin fietsers en andere gebruikers van micromobiliteit in hun eigen tempo kunnen rijden zonder door anderen te worden beïnvloed. Dit is belangrijk omdat snellere fietsers nu relatief meer vertraging ondervinden door het huidige netwerk. Het is ook relevant voor de verkeersveiligheid, aangezien interacties tussen weggebruikers met verschillende snelheden risico's kunnen opleveren, zeker voor kwetsbare groepen. Voor zo'n inclusief netwerk is voldoende ruimte noodzakelijk om verschillende micromobiliteitsgebruikers te accommoderen, bijvoorbeeld via brede fietspaden en fietssnelwegen. Daarnaast zijn regelgeving en gedragsafspraken essentieel, zoals links blijven bij inhalen en snelheidslimieten op smalle wegen, om kwetsbare weggebruikers te beschermen.

Chapter 1: Introduction

1.1 Cycling and Cycling Speed

Cycling improves individuals' accessibility and health, and reduces congestion and transportation emissions at the societal level (Heinen et al., 2010). Therefore, it is promoted worldwide (Buehler & Goel, 2022). In practice, policies targeting society (e.g., restricting car use), city settings (e.g., mixed-land use), bicycle infrastructure (e.g., physically separate bike lanes), and individuals (e.g., monetary incentives) are implemented (Winters et al., 2017). In research, cycling-related studies are conducted to understand different aspects of cycling, such as the choice between cycling and motorised modes (Heinen et al., 2012), route choice (Łukawska, 2024), the use of electric bicycles (Van der Salm et al., 2022), bicycle infrastructure (Rayaprolu et al., 2018), cycling safety (Poudel & Singleton, 2021) and cycling equality (Cunha & Silva, 2022). In the meantime, bicycle production, ownership and use have increased worldwide (Chen et al., 2022).

Cycling speed is closely related to travel time and influences the attractiveness of cycling (Flügel et al., 2017). For a given route, higher speeds reduce travel time, increasing the accessibility of cyclists and the attractiveness of bicycle networks (Geurs & van Wee, 2004; Romanillos & Gutiérrez, 2019). In addition, travel time is regarded as a disutility (Koster & Koster, 2015), which means that higher speeds make cycling and routes more attractive. Since people make travel choices to maximise their utility, speed is also expected to influence other cycling choices, such as mode and route choices (Berjisian & Bigazzi, 2025). Although cycling speed is associated with accident frequency and injury severity (Schepers et al., 2017), removing the hindrance to smooth cycling and improving cycling speed are believed to increase the competitiveness of cycling compared to motorised transport modes (Clarry et al., 2019; Strauss & Miranda-Moreno, 2017).

Cyclists also positively value speed, illustrated by the widespread use of electric bicycles. In Europe, electric bicycles are distinguished between regular electric bicycles, which support pedalling up to 25 km/h, and speed pedelecs, supporting pedalling up to 45 km/h (Schleinitz et al., 2017). These bicycles help cyclists to maintain a higher speed with less effort. Take the Netherlands as an example: in 2021, 20% of the population owned at least one electric bicycle (Huang et al., 2024), and e-bike ownership is expected to continue growing. New types of bicycle infrastructure, such as green waves and bicycle highways (Rayaprolu et al., 2018), are introduced to support smooth cycling at high speeds. These bicycles and infrastructure not only increase the overall speed but also lead to speed differences between cyclists and routes, complicating cycling behaviour.

In addition to speed itself, speed stability influences the attractiveness of cycling, as it is related to travel time, required effort and safety. Berjisian and Bigazzi (2025) identified cruising events, where cycling speed is relatively stable, from GPS-tracked cycling trips, and their speeds are significantly higher than the speed of unstable events. This indicates that the stability in speed reduces travel time for the given routes. This is also illustrated by the significant delays at intersections, where deceleration and re-acceleration are always involved (Strauss & Miranda-Moreno, 2017). During such unstable phases, extra physical and mental effort is inherently required. In addition, these speed changes, especially speed decrease due to heavy braking, can lead to balance loss and crashes over the handlebars (Schepers & Wolt, 2012), posing safety issues. Therefore, stable speeds increase the utility of cycling and are preferred by cyclists (Joo et al., 2015).

Due to the importance of cycling speed, some studies have explored its determinants, dating back to 1980 (Opiela et al., 1980) and especially from 2015 (e.g., Romanillos & Gutiérrez, 2019; Yan et al., 2024). These studies measured cycling speed from different aspects, including bicycle flow speeds (e.g., Jin et al., 2017) and individual speeds (e.g., Flügel et al., 2017). Regarding the unit of observations, individual speeds were measured as average trip speeds (e.g., Jensen et al., 2010), average speeds at route segments (e.g., El-Geneidy et al., 2007) and instantaneous speeds at tracking points (e.g., Clarry et al., 2019). A finer study unit can better reflect the real speed variation during rides, but only a few studies have examined instantaneous speeds. In addition, longitudinal speed stability during a ride has hardly been measured and explored. Regardless of how speed was measured, these studies mainly examined the direct influence of a limited number of determinants, such as gender, age, bicycle types, bicycle infrastructure and land use. A comprehensive understanding of cycling speed, including its related factors and complex relationships, is still lacking. This suggests that existing exploration of cycling speed choices remains fragmented, lacking an examination of detailed speed variations and speed stability during the ride, and a wide range of determinants.

This thesis therefore aims to expand understanding of cycling speed, both qualitatively and quantitatively. The main focuses include (1) a conceptual model of cycling speed to illustrate the process through which cycling speed of a trip is determined, (2) the study designs employed in examining determinants, (3) detailed speed variations and speed stability within a ride, and (4) a wide range of determinants, including factors fixed to the locations, such as bike infrastructure and land use, and factors changing over time, like weather conditions. By doing so, this thesis addresses five scientific gaps, which are illustrated in the following section.

1.2 Knowledge Gaps

Cycling speed is increasing and becoming increasingly diverse due to the introduction of new types of bicycles and bicycle infrastructure. This trend influences bicycle attractiveness. Therefore, some studies explore the determinants of cycling speed (e.g., Berjisian & Bigazzi, 2025). Although these studies provide insights into cycling speed and its determinants, some limitations still exist:

- **Gap 1 is the lack of a comprehensive understanding of how the cycling speed of a trip is determined, including the related factors and relationships**

Cycling speed is a complicated topic. It is influenced by the characteristics of cyclists, bicycles and contexts, as well as various cycling choices, such as bicycle mode, cycling route and destinations. Cycling speed also affects individuals' accessibility, health and safety, which further influence their characteristics, such as preferences and attitudes. This means that cycling speed is embedded in a feedback loop. Despite an increasing number of studies examining cycling speed, a complete explanatory model of cycling speed, including its related factors and the complex relationships, is unavailable. Without understanding this model, studies are likely to ignore some important factors and relationships, resulting in biased results.

- **Gap 2: A review of study designs employed for examining cycling speeds' determinants is missing**

Study designs are crucial for obtaining accurate results regarding the determinants of cycling speed. Existing studies, however, vary widely in study design, including data collection strategies, speed measurement and analytical methods. This variation makes it challenging to compare the results of different studies and draw a comprehensive conclusion. In addition, different study designs have their own advantages and disadvantages, making them suitable for specific situations. Therefore, a systematic review on this aspect is necessary.

- **Gap 3: Knowledge about cycling speed variation within a trip is insufficient, and a comprehensive examination of a wide range of determinants, including the characteristics of cyclists, trips, and route conditions, is lacking**

Most existing studies focused on the bicycle flow speed at specific locations (e.g., Jin et al., 2017) or the average speeds of trips/route segments (e.g., Jensen et al., 2010; Romanillos & Gutiérrez, 2019). However, cycling speed not only varies between cyclists or trips, but also changes constantly during the trip, partly depending on the attributes of bicycle infrastructure and land use. Understanding this variation can help recognise the attributes that support or prevent smooth cycling and provide urban and transportation planners with information for a more attractive cycling system. This detailed speed variation during a ride has been underexplored (Arnesen et al., 2019; Belikhov et al., 2025; Clarry et al., 2019).

Cycling speed is influenced by characteristics of cyclists, bicycles, routes and contexts. Simultaneously including these factors in a statistical model can effectively detect their separate effects and avoid the confounding results. Most existing studies, however, focused on specific ones, such as bicycle type (Schleinitz et al., 2017) and slopes (Parkin & Rotheram, 2010). In addition, many factors, such as individual preferences, which have been proven to be important in travel choices (Van Wee et al., 2019), have largely been overlooked.

- **Gap 4: Speed variation due to factors varying over time, especially weather conditions, has hardly been examined**

Compared to factors fixed at the routes, those varying over time, such as weather conditions, influence not only travel time (speeds within a trip), but also travel time reliability (speeds of repeated trips). Travel time reliability refers to the temporal (un)certainty of the travel time of a route experienced by travellers, for example, measured from day to day (Sweet & Chen, 2011). For a given route, a relatively reliable travel time allows travellers to easily arrange their trip decisions, such as departure time. By contrast, unreliable travel times can lead to uncertainty, anxiety and dissatisfaction, being regarded as a disutility (Bhat & Sardesai, 2006). Many studies even conclude that travel time reliability plays a more important role in travel choices than travel time (Zang, 2021). Varying weather conditions make the speed and travel time of the same route inconsistent and unreliable, causing disutility.

The influence of weather on cycling speed and travel time reliability is exacerbated by climate change. Due to climate change, temperatures, wind speeds and rainfall are expected to increase (Held & Soden, 2006; McInnes et al., 2011), and extreme weather conditions, such as heatwaves and intense precipitation, will occur more frequently (Rummukainen, 2012). These weather changes discourage cycling and complicate cycling speed choices. However, only a few studies have explored this topic (Maurer et al., 2025; Pérez Castro et al., 2025), and a comprehensive exploration, involving a rich set of weather conditions, is missing.

In addition, the influence of weather on cycling behaviour has been proven to vary across cyclists (Nordbakke & Olsen, 2019) and places (Helbich et al., 2014), showing cyclist and geographic heterogeneity. Cyclists have different perceptions of cycling and weather, and varying physical conditions, bicycles, and other cycling-related equipment. This means that they have different levels of acceptance of the weather, and they are influenced by the weather to different extents. The objects on the ground, such as buildings and vegetation, can change microclimate conditions, resulting in varied weather exposures across space. Heterogeneity is a major source of confounding, and ignoring it can lead to biased results when examining the influence of weather on cycling behaviour, including cycling speed. However, this has been overlooked.

- **Gap 5: Cycling speed stability and its determinants are hardly examined.**

Speed changes frequently during a ride, such as slowing down before red lights and speeding up after turns. This speed change reflects the extent to which the speed of a trip is stable. Unstable cycling speed has a number of consequences: longer travel time (Berjisian & Bigazzi, 2025), high risks, extra physical effort, and lower trip satisfaction (Joo et al., 2015), which will decrease the competitiveness of cycling. However, studies on speed stability, including its definition, identification and determinants, are lacking for cycling and even for other transport modes. Knowledge of cycling speed stability and its determinants can be applied in urban and transportation planning, enabling cyclists to ride smoothly.

1.3 Aims and Research Questions

Based on the gaps identified, the overarching aim of this research is as follows:

To advance understanding of variation and stability in cycling speed within a ride and their determinants.

To fulfil this aim, five sub-research questions are formulated. The first two provide explanatory and methodological foundations for the three empirical questions, which focus on different determinants of variation and stability in cycling speed:

1. What determinants and relationships are involved in determining cycling speed during a trip? (Chapter 2)
2. What do we know about study designs used to examine the determinants of cycling speed? (Chapter 3)
3. How do the characteristics of cyclists, trips and route tracking points influence cycling speed variation within a trip? (Chapter 4)
4. How do weather conditions influence cycling speed? What are the roles of cyclist weather-sensitivity and spatial conditions? (Chapter 5)
5. What are the patterns of cycling speed stability and disruption, and their determinants? (Chapter 6)

1.4 Theory

Cycling speed is influenced by the characteristics of cyclists, bicycles, the physical environment and contexts. While no single theory fully explains cycling speed, several theoretical perspectives offer valuable insights for this research. Specifically, utility-based theories highlight that a reduced travel time due to a higher cycling speed increases utility, and cyclists choose their speed by balancing trade-offs between time, effort, comfort, and safety to maximise the overall utility; traffic flow theory and planned behaviour theory provide insights into the determinants that can possibly influence cycling speed. Together, these perspectives inform the conceptual framework of this research and guide the analysis of each sub-research question.

Utility-based theories

In transport economics, travel time is often regarded as a disutility (Koster & Koster, 2015), since time spent travelling reduces the time available for other activities. This is reflected in the concept of the *Value of Travel Time Savings (VTTS)*, namely, the monetary value that individuals or society is willing to pay to reduce travel time (Small, 2012). The increase in the sales and use of electric bicycles (Chen et al., 2022), which are faster and more expensive than city bicycles, shows the relevance of VTTS to cycling speed.

This research, therefore, assumes that, other things being equal, increasing overall cycling speed benefits cyclists by saving time and enhances the competitiveness of cycling relative to motorised modes. However, this does not imply promoting ever-higher speed, as it can also cause disutility, such as accidents. *Expected Utility Theory* and *Random Utility Theory* assume that individuals act rationally to maximise their utility (Ramos et al., 2014). Cycling speed can be seen as the outcome of a utility-maximising process. Cyclists balance the benefits of higher speed (e.g., shorter travel time) against the costs (e.g., greater physical effort and increased safety risks). The chosen speed represents the point at which marginal benefits equal marginal costs, yielding the highest overall utility.

In addition to time savings, travellers value reliability in travel time, known as the *Value of Travel Time Reliability* (Carrion & Levinson, 2013). Particularly for commuting, consistent and predictable travel time enables reliable scheduling of activities. Uncertainty, by contrast, reduces utility and may generate stress (e.g., from the risk of lateness). It indicates the importance of considering factors that can cause speed variation across trips, especially weather conditions. This is especially relevant to research question 4.

Traffic flow theory

Speed variation and speed stability are the situations in which vehicles deviate from or maintain their *free-flow speed*. Free-flow speed of a car occurs when the driver-vehicle combination drives under uninterrupted situations, and this speed depends on the characteristics of the driver, the vehicle, the route and the contextual conditions (Hoogendoorn, 2005). Applied to cycling, it can be expected that cycling speed and its stability are influenced by the same factors: the characteristics of cyclists, bicycles, the environment, contexts and other road users. This theory helps to select potential determinants to answer all three empirical research questions.

Theory of planned behaviour

The theory of planned behaviour (TPB) indicates that behaviour is shaped by attitudes, subjective norms, and perceived behavioural control. For cycling speed, attitudes towards speed and safety play a direct role: individuals who enjoy speed tend to cycle faster, while those prioritising safety are more likely to cycle at a slower pace. This idea is considered to answer the third research question.

The TPB is also used to answer research question 4: the influence of weather on cycling speed. In adverse weather conditions, whether individuals choose to cycle depends not only on the weather conditions but also on their attitudes toward cycling and their perceived behavioural control under such conditions. Accounting for this phenomenon is important, as individual attitudes are important confounders of weather conditions when examining their influence on cycling speed.

1.5 Research Data and Approach

This research utilises quantitative data to address the three empirical research questions (RQs 3-5) in Chapters 4-6. The cycling datasets used for them are different but have the same nested data structure. Therefore, the statistical methods employed to answer these research questions are similar. This section describes the data and methods separately.

1.5.1 Data

Cycling data are the core of this research. As the aim is to explore cycling speed variation and stability within rides and their determinants, the cycling data need to capture detailed speed profiles along the ride. Therefore, this research uses datasets with cycling trips tracked by GPS devices, which continuously register their positions and timestamps (every several seconds). The registered observations are called tracking points. Their speeds can be calculated with the positions and timestamps of the consecutive tracking points.

Different cycling datasets are used to answer three empirical research questions (Table 1.1). The data for RQ 3 were collected in 2020. Because of Covid-19, a random sampling was virtually impossible, so we had to follow a less formal approach to recruit participants. Three master students recruited their relatives and friends for this study. In total, 60 people participated in the study and made 508 bicycle trips. In addition, participants completed a questionnaire about their sociodemographics, bicycle ownership and cycling speed-related preferences. For RQs 4 and 5, the cycling data of the Sniffer Bike project (Snuffelfiets, 2020) was used. The project aims to support research to expand the knowledge about cycling and the physical environment, starting in June 2019 and is still ongoing. RQ 4 excludes data for 2020, when daily travel was significantly influenced by Covid-19, so it utilises the subset from January 2021 to October 2023. After data filtering, the dataset comprises 224 cyclists who made 65,196 rides, consisting of 5,260,355 tracking points. RQ 5 uses the cycling data from 2020. After data filtering, there are 5,672,552 tracking points from 59,928 trips of 505 cyclists. Although Snuffelfiets is a rich dataset, it is also limited because respondents participate anonymously, and the characteristics of participants and bicycles are not recorded.

Table 1.1: The datasets used for empirical research questions

	RQ 3: Determinants of cycling speed variation (Chapter 4)	RQ 4: Weather's influence on cycling speed (Chapter 5)	RQ 5: Determinants of cycling speed stability and interruptions (Chapter 6)
Cycling data	Self-collected	Sniffer Bike project (01.2021-10.2023)	Sniffer Bike project (2020)
Bike infrastructure	Cyclists' Union (Fietsersbond, 2018)		
Land use	Bestand Bodemgebruik 2015 (CBS, 2015)		
Altitude	Actueel Hoogtebestand Nederland (AHN, 2020)		
Weather	KNMI		--
Building	--	3DBAG, 2023	--

Cycling speed and its stability are both influenced by bicycle infrastructure, land use, and slope, so the three chapters share the datasets of these independent variables (Table 1.1). Bicycle infrastructure attributes are derived from the Cyclists' Union (Fietsersbond, 2018), including bike lane types, intersections, turns, bridges and tunnels, while land use data are derived from the Bestand Bodemgebruik 2015 (CBS, 2015). Slope is calculated with the altitude from a 0.5*0.5 metre resolution altitude map of the Netherlands (AHN, 2020). In addition, to answer RQs 3 and 4, the same weather dataset was used, from the Royal Netherlands Meteorological Institute (KNMI, 2020), which records the finest and most accurate weather data in the Netherlands.

An exception is the building dataset (3DBAG, 2023), which is used only for RQ 4. The influence of weather on cycling speed is assumed to be moderated by the shelter caused by objects on the grounds. Buildings are the major source of shelter, and this dataset is used to calculate the shelter value.

1.5.2 Research approaches

In current cycling datasets, participants track their cycling trips using a GPS device, and each trip consists of multiple tracking points, resulting in a three-level nested data structure (cyclists, trips, and tracking points). The observations nested in a higher level share the same attributes; for example, tracking points of a trip have the same trip characteristics, such as trip purposes. In other words, observations in the current datasets are not fully independent, and this dependence needs to be addressed to obtain unbiased results. Three-level multilevel models are particularly well-suited to the current nested datasets, as they introduce random intercepts for each group (the trip for tracking points, and the cyclist for trips), which capture the unobserved attributes shared by the observations within the group (Searle et al., 2009). Therefore, multilevel models are estimated to answer three empirical research questions (Chapters 4-6), and some differences exist depending on the type of the dependent variable in each chapter (Table 1.2).

Table 1.2: The research methods used for empirical research questions

	RQ 3: Determinants of cycling speed variation (Chapter 4)	RQ 4: Weather's influence on cycling speed (Chapter 5)	RQ 5: Determinants of cycling speed stability and interruptions (Chapter6)
Statistical method	Three-level linear mixed-effect model		Two-level multinomial logistic model
Other tools	--	Factor mixture model: recognising different weather sensitivity groups	1 Pruned Exact Linear Time algorithm: trip segmentation based on the speed stability 2 Rule-based algorithms, recognising speed (un)stable patterns

Chapter 4 estimates three-level linear mixed-effect models (Leckie, 2013) to answer RQ 3, as the dependent variable, namely cycling speed, is linearly measured. Chapter 5 employs the same method for RQ 4. In addition, it assumes different weather sensitivity groups, which are different in (1) the weather conditions under which they make bicycle trips and (2) the extent to which their speeds are influenced by weather components. To identify these weather sensitivity groups, factor mixture models (FMM) (Clark et al., 2013) are estimated.

RQ 5 is about cycling speed stability and interruptions. It requires detecting and recognising different (un)stable segments from bicycle trips. To achieve this, a change point detection method, in particular, the Pruned Exact Linear Time (PELT) algorithm (Truong et al., 2020), is adopted to divide trips into segments differing in the extent of speed stability. Then, a rule-based algorithm is developed to classify these segments into the stable pattern and five unstable patterns. These six patterns form a categorical dependent variable, which requires a multinomial logistic modelling technique. Although this dataset has three levels, a three-level model failed to converge, possibly due to small differences between cyclists. Therefore, a two-level (trips and tracking points) multinomial logistic model (Hedeker, 2003) is estimated to examine the determinants of different speed patterns.

1.6 Contributions and Relevance

Speed is a core attribute of a transport mode, and speed choice is highly related to other travel behaviour (Flügel et al., 2017). However, speed has hardly been studied, both for cycling and other transport modes. This research aims to explore cycling speed variation and speed stability, which contribute to both scientific knowledge and societal practice.

1.6.1 Contributions to science

This research fills the gaps in the cycling speed-related topics, and each chapter 2 to 6 contributes differently, as described below:

Chapter 2: Cycling speed: conceptualisation and research agenda

This chapter proposes a novel conceptual model of cycling speed. This model explains the feedback loop in which cycling speed is embedded, involving its determinants (individual characteristics, context and trip choices) and its effects (accessibility, safety, health and wellbeing). Its effects, in turn, influence individual characteristics, such as physical condition and attitudes. Complicated relationships between these factors are also illustrated in the model. Such a model not only reveals the comprehensive mechanisms behind the determination of cycling speed but also highlights important research directions that have been overlooked.

Chapter 3: Examining the determinants of cycling speed: a review of study designs

This chapter reviews study designs employed in exploring the determinants of cycling speed. Based on study designs, it classifies existing studies into three categories and provides an understanding of the advantages and disadvantages associated with each category. This helps future research choose the most appropriate study design.

Chapter 4: Cycling speed variation: a multilevel model of characteristics of cyclists, trips and route tracking points

This chapter expands the understanding of cycling speed variations during a ride by using a cycling dataset collected with GPS devices. This addresses the gap that most existing studies examine aggregated speeds and average speeds (e.g., Boufous et al., 2018; Jensen et al., 2010; Jin et al., 2017). In addition, the influence of a wide range of determinants, including cyclists (socio-demographics and preferences), trips (bicycle types, departure time and trip purposes), and route tracking points (land use and bicycle infrastructure), on cycling speed at tracking points is simultaneously examined. This explains the intra-trip speed variation.

Methodologically, multilevel linear regression models are estimated to account for the dependence of observations, which is largely neglected by existing studies. The inclusion of random intercepts for each trip and cyclist allows the exploration of inter- and intra-cyclist speed variation.

Chapter 5: Cycling speed and weather: Roles of cyclist weather-sensitivity, spatial and infrastructural conditions

This chapter addresses the lack of a comprehensive understanding of how weather influences cycling speed. It contributes by comprehensively examining a wide range of weather components, including temperature, precipitation, wind (headwinds, crosswinds, and tailwinds), humidity, fog, ice and snow.

This chapter also advances understanding of both cyclist heterogeneity and geographic heterogeneity in responses to weather. By identifying three distinct weather-sensitivity groups, it contributes to a more nuanced understanding of how cyclists differ in their reactions to various weather conditions. Furthermore, by incorporating wind shelter as an indicator of spatial context, the study extends existing approaches to account for geographic heterogeneity. Together, these contributions provide a more comprehensive framework for analysing how weather and environment jointly influence cycling speed.

Chapter 6: Explaining patterns of cycling speed stability and disruption

This chapter investigates cycling speed stability. Theoretically, it introduces and defines the concept of cycling speed stability as the extent to which cyclists maintain stable speeds during the ride. Methodologically, it extends existing approaches to speed measurement by focusing on longitudinal changes in speed within a trip. A method is developed to identify trip segments exhibiting different extents of speed stability and to classify these speed patterns. Furthermore, the circumstances under which different speed patterns occur are explored, with a particular focus on bicycle infrastructure and land use. This provides a new perspective for quantitatively evaluating bicycle networks.

1.6.2 Societal relevance

Higher and stable cycling speeds reduce travel time and increase the competitiveness of cycling compared to other motorised transport modes. By investigating the determinants of cycling speed and its stability, this research recognises the factors that cause significant speed loss and destabilise cycling speed. With such knowledge, urban planners, road constructors and policymakers can formulate corresponding policies to support smooth cycling, therefore increasing cycling satisfaction and the bicycle share.

Specifically, **Chapter 4** provides detailed information about the influence of bicycle infrastructure and land use on cycling speed, which can support the design and construction of bicycle infrastructure. **Chapter 5** recognises the weather components that adversely influence cycling speeds, providing insights for policies aimed at protecting cyclists from bad weather conditions. Additionally, by investigating the geographic heterogeneity of weather's influence, it can identify the specific infrastructure or land use designs that protect cyclists from bad weather conditions. **Chapter 6** explores cycling speed stability and its determinants. It supports planners in building smooth bicycle infrastructure on the one hand, and provides a new dimension for evaluating bicycle infrastructure on the other hand.

In addition to contributing to policies, the results of this research can be used in navigation apps (1) to accurately predict the required travel time of different routes, (2) to find routes according to users' preferences for speed and speed stability, and (3) to find suitable routes under different weather conditions to reduce the negative influence of weather. Most cyclists may not be familiar with all the routes around them; in addition, they may not have a precise understanding of the speeds or travel times under different route conditions and weather situations. It means that making an optimal choice of departure time and route is not easy. Navigation apps with this function can help cyclists make informed route choices and maximise the use of existing bicycle infrastructure according to their preferences.

1.7 Thesis Outline

This thesis explores cycling speed, speed stability, and their determinants. Chapter 2 proposes and underpins a conceptual model of cycling speed, outlining its related factors and complex relationships among them, with relevant literature (research gap 1). Chapter 3 reviews study designs used in examining the determinants of cycling speed (research gap 2), providing a foundation for our study design choices.

Chapters 4 and 5 uncover the determinants of cycling speed variations within a ride, using two different datasets from the Netherlands. Chapter 4 focuses on the factors that are fixed to the route (research gap 3), including bicycle infrastructure, land use and road gradients. Building on this, Chapter 5 considers the determinants that change over time (research gap 4), using weather conditions as an example. Chapter 6 investigates cycling speed from a longitudinal perspective, namely speed stability within a ride, and the determinants of different speed stability patterns (research gap 5).

This thesis concludes with a summary of the main findings, their implications and future research directions in Chapter 7.

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Chapter 2: Cycling Speed: Conceptualisation and Research Agenda

2.1 Introduction

Cycling, as an active transport mode, benefits both individuals and society (Heinen et al., 2010). For individuals, cycling is a competitive alternative to motorised modes for short trips in urban areas (Larsson et al., 2022; Romanillos & Gutiérrez, 2019). Cycling involves physical activity that can promote health and reduce overweight/obesity (Oja et al., 2011). Although cyclists are affected more seriously by accidents and have a higher exposure to air pollution than motorised vehicle users, the overall health benefits substantially outweigh the risks (De Hartog et al., 2010; Van Wee & Ettema, 2016). Furthermore, compared to private cars and public transport, bicycle commuting brings on average higher travel satisfaction and better mental health, such as lower stress levels (Berrie et al., 2024; Liu et al., 2022). Regarding society, replacing short car trips with cycling reduces traffic emissions (Neves & Brand, 2019) and mitigates traffic congestion (Hamilton & Wichman, 2018). Therefore, cycling is promoted throughout the world (Handy et al., 2014).

In response to rising attention to cycling, increasing numbers of studies focus on various aspects of cycling behaviour, including the choice between cycling and motorised modes (Heinen et al., 2012; Huurman et al., 2024; Ton et al., 2019), cycling route choice (Łukawska, 2024) and cycling safety (Poudel & Singleton, 2021). Although speed is an important attribute of cycling, it has long been ignored (Flügel et al., 2017; Yan et al., 2024).

Speed influences travel time. For a given bicycle network, higher cycling speeds imply better accessibility by bicycle, with reduced travel times and greater opportunities to reach various activities (Geurs & van Wee, 2004). In transport economics, travel time is considered a disutility (Koster & Koster, 2015), especially for commuting trips, so the (expected) cycling speed can affect individuals' travel choices, such as the mode and route. The decrease in travel time of a transport mode is associated with the increase in its mode share (Frank et al., 2007). Similarly, longer travel time is one of the most disfavoured attributes in bicycle route choices (Liu et al., 2025; Sener et al., 2009). This illustrates that by removing barriers to smooth cycling and improving cycling speed, cycling can be made more attractive and competitive.

Cycling speed also affects other benefits for individuals. Speed is positively related to the physical activity intensity during cycling (De Geus et al., 2007), and therefore to health. A relatively high and stable speed increases the satisfaction of cyclists compared to a low and varied speed (Joo et al., 2015). However, higher cycling speed is not always a positive characteristic, as it is associated with higher accident rates and injury severity (Schepers et al., 2017).

Due to the benefits of cycling speed, new bicycle infrastructure, like bicycle highways (Rayaprolu et al., 2018) and green waves, as well as new bicycle types, including regular electric bicycles and speed pedelecs (Schleinitz et al., 2017), have been introduced. These new types of infrastructure and bicycles not only increase overall cycling speed but also expand cycling speed differences between cyclists and between places, bringing both opportunities and challenges to cyclists and the bicycle system. Correspondingly, studies that explore the determinants of cycling speed have emerged (Clarry et al., 2019; El-Geneidy et al., 2007; Pérez Castro et al., 2025; Yan et al., 2024), especially due to the affordable GPS technology, which can track accurate time and location stamps for speed calculation (Bohte & Maat, 2009).

Despite the growing number of studies, our understanding of the causes and influences on variations in cycling speed remains incomplete. Most existing studies have focused on only the direct influence of specific factors, such as intersections (Strauss & Miranda-Moreno, 2017) and bike lane types (Boufous et al., 2018), on cycling speed. However, cycling speed is a complex phenomenon. It is not only a deliberate choice, but also the result of an intention to achieve a certain speed, which is enabled or limited by the characteristics of cyclists, bicycles, the context, infrastructure, and other cycling choices, such as route choice. Speed also influences individuals' accessibility, health, and well-being, which may in turn change their physical condition and attitudes. Between these factors, complicated relationships exist. A comprehensive explanatory model of cycling speed can illustrate how the speed of a trip is determined by these factors and their interactions. It can help researchers identify essential determinants and relationships that are often overlooked. Such a model, however, is unavailable.

Therefore, the current literature review aims to (1) build a conceptual model of cycling speed to illustrate its related factors and relationships between them as completely as possible; and (2) propose a research agenda for future studies on cycling speed. To achieve these aims, we draw on evidence from the literature to support the conceptual model and inform the research agenda, following an approach similar to that of Van Wee and Ettema (2016), rather than providing a comprehensive overview of all studies on all relationships.

The following section describes and underpins the conceptual model of cycling speed to achieve the first aim, which is followed by the main findings and discussion in Section 2.3. A research agenda is provided in Section 2.4 for the second aim. The paper ends with a conclusion.

2.2 Conceptual Model

2.2.1 Scopes and definitions

In this section, using the literature, a conceptual model is developed to explain the process underlying cycling speed, including its determinants and effects (Figure 2.1). First, to meet the mobility needs and desires, individuals make several trip choices, such as purpose and bicycle type, based on context and individual characteristics. A trip inherently results in cycling speed. Second, speed can impose various effects, such as on accessibility and health. These effects can, in turn, shape certain individual characteristics, including physical condition and attitudes, either immediately or cumulatively. These two parts form a feedback loop involving cycling speed.

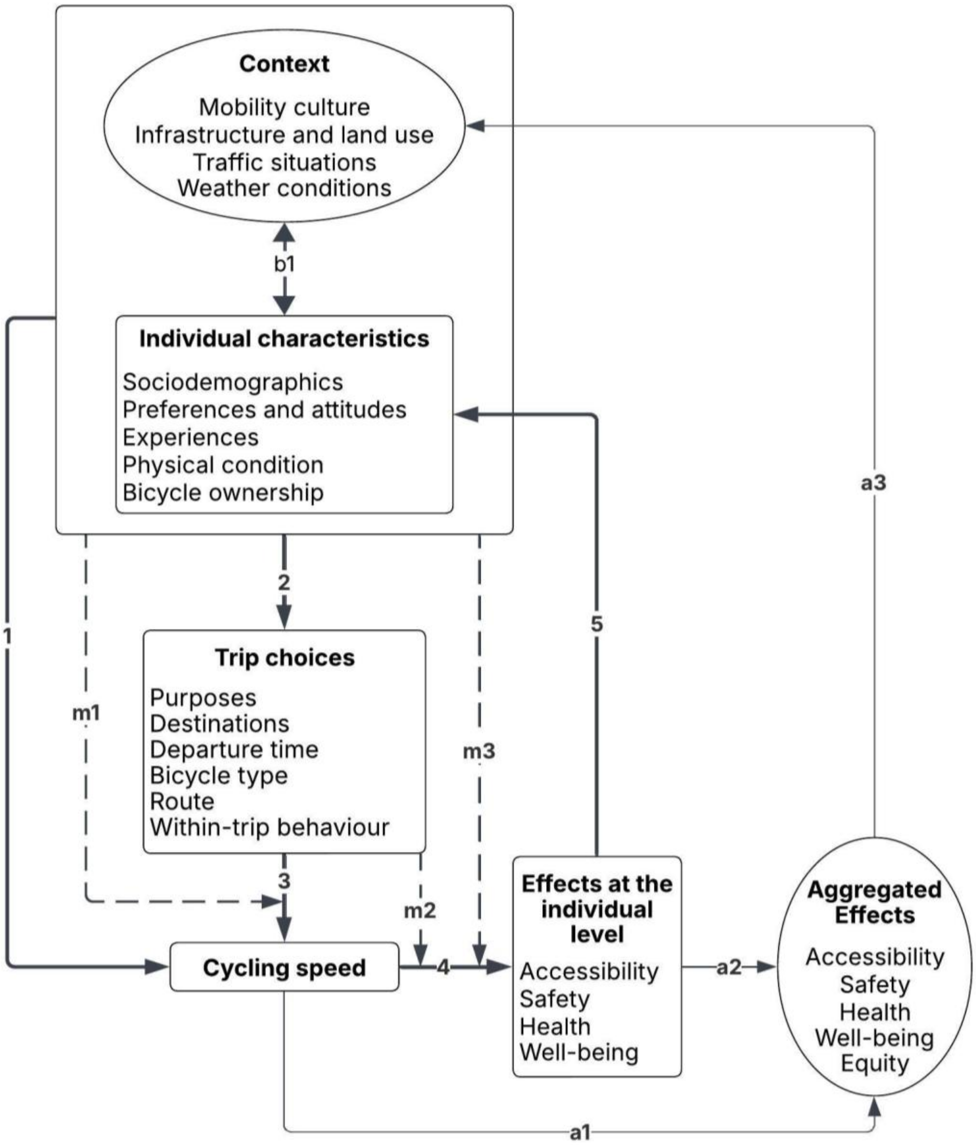

Figure 2.1: Conceptual model of cycling speed

2.2.1.1 Components

The conceptual model comprises five components: background (context and individual characteristics), trip choices, cycling speed, the effects of speed on a cyclist and the aggregated effects on all cyclists. Each component includes several factors. The trip-specific and individual components are illustrated with rectangular blocks, while the aggregated components (context and aggregated effects) are shown as ovals.

Cycling speed is the core variable of the model. Its meaning varies depending on the units of observation: the average speed for a trip (e.g., Schleinitz et al., 2017) or a trip segment (e.g., El-Geneidy et al., 2007), instantaneous speed across locations (e.g., Arnesen et al., 2019) and speed changes over a period of time (e.g., Berjisian & Bigazzi, 2025). Despite their different meanings, these observed speeds are influenced by similar determinants (Arrows 1 and 3). Therefore, the conceptual model uses the term 'cycling speed' to collectively denote all speed observations rather than considering them separately. Moreover, although speed is inherently embedded in various trip choices, it is considered separately due to its central role in the current model, connecting determinants and outcomes.

Context and individual characteristics fundamentally influence cycling speed and trip choices. The context refers to the characteristics of the residential area and cycling route, including mobility culture, environment (bicycle infrastructure, land use, and weather conditions), and traffic situations. Individual characteristics include socio-demographics, preferences and attitudes, cycling-related experiences, physical condition, and bicycle ownership.

Trip choices are trip-specific, including the purposes and destinations (one or more), bicycle type, departure time and route, as well as in-ride behaviour (e.g., cell phone use).

The block of effects refers to the immediate outcomes of the speed of a trip or a specific moment within a trip. It includes accessibility (e.g., travel time), safety (e.g., traffic accidents), health (e.g., energy boost and pollutant intake) and well-being (e.g., stress release and trip satisfaction). The aggregated effect further captures system-level implications related to all cyclists, such as cycling congestion, potential traffic accidents caused by interactions between cyclists with different speeds, and the related equity issue that vulnerable cyclists are disproportionately affected when accidents occur.

2.2.1.2 Relationships in general

Between these components, five basic relationships (Arrows 1-5) constitute the feedback loop. Context and individual characteristics directly (Arrow 1) and indirectly via trip choices (Arrows 2 and 3) influence cycling speed, inherently producing several effects (Arrow 4), which ultimately affect individual characteristics (Arrow 5).

Arrows 1-4 describe trip-specific relationships, while Arrow 5 is both trip-specific and mainly individual-specific. Trip-specific influences operate for a single trip, while individual-specific influences consider the cumulative effects of a cyclist's long-term cycling. For Arrow 5, the trip-specific influences occur due to strong events, such as serious accidents, which immediately change an individual's physical condition and attitudes. The individual-specific influences are relatively common, as physical condition, attitudes, and preferences are gradually shaped due to long-term cycling. When Arrow 5 operates at the trip level, the feedback loop closes once, and the conceptual model illustrates the process by which the cycling speed of a trip is determined. On the contrary, when Arrow 5 operates at the individual level, the feedback loop recurs multiple times, illustrating how an individual's long-term speed behaviour develops.

Three major moderation effects (Arrows m1-m3) are included, where 'm' denotes moderation. Arrow m1 indicates that the relationships between trip choices and cycling speed are moderated by context and individual characteristics; for example, the positive effect of using an electric bicycle on cycling speed differs across cyclists. Arrow m2 shows that the relationship between cycling speed and its effects is moderated by trip choices; for instance, e-bike riders experience lower health benefits than city bike riders at the same speed. Arrow 3 indicates that this relationship also depends on context and individual characteristics; for example, vulnerable cyclists tend to be injured more seriously than strong cyclists when involved in an accident at the same speed. All moderation relationships are trip-specific.

Two major bidirectional relationships are identified. First, different trip choices (the block of Trip choices) influence each other. For a trip, cyclists make interdependent decisions about purpose, destination, route, and departure time, rather than treating each choice independently. Second, the context and individual characteristics influence each other (Arrow b1), where 'b' represents 'bidirectional'. It is individual-specific and occurs only when Arrow 5 is individual-specific. It captures individuals' residential choices and the shaping of their preferences and attitudes in response to contexts.

Three aggregated relationships describe the collective effects on/of all cyclists (Arrow a1-a3), where 'a' denotes aggregation. This review focuses on the trip and individual-related mechanisms and will not discuss the aggregated relationships.

Additional relationships exist between cycling speed-related factors. For example, trip choices directly affect accessibility and health. Sub-factors within a component also influence each other; for instance, weather, infrastructure and land use affect traffic conditions, and bicycle ownership is influenced by income and household context. We acknowledge the existence of these relationships but focus on the most direct and conceptually relevant pathways to maintain clarity.

The following sections underpin basic (Sections 2.2.2 to 2.2.7), moderation (Section 2.2.8) and bidirectional relationships (Section 2.2.9).

2.2.2 Context and cycling speed (arrow 1)

Each society or region has a distinctive mobility culture (Te Brömmelstroet et al., 2020), shaped by its physical environment, social norms, and individuals' perspectives of mobility. Cycling culture is a part of mobility culture and tends to determine the typical cycling speed of a place. Despite no direct evidence for this relationship, the substantial differences in cycling speed across places (Lin et al., 2008; Schepers et al., 2017) suggest this possibility.

The bicycle infrastructure and land use-related factors can be grouped into those present along entire trips, like bicycle lane types and land use (Berjisian & Bigazzi, 2025), and those occurring at specific locations, such as intersections and turns (Strauss & Miranda-Moreno, 2017). Statistically, location-specific factors have a relatively big effect on cycling speed (Yan et al., 2024), while the factors existing along the entire route exert cumulative effects over the trip. Here, we focus on the directions of these effects rather than comparing their overall magnitude.

The factors along the entire route include bicycle lane types, infrastructure design, gradients, and land use. Physically separated lanes protect cyclists from other road users, enabling higher speeds compared to lanes shared with motorised vehicles (Clarry et al., 2019; El-Geneidy et al., 2007; Flügel et al., 2017; Opiela et al., 1980) or pedestrians (Romanillos & Gutiérrez, 2019; Schuhmacher et al., 2025; Zhe et al., 2008). A study in Ottawa, Canada, reported a 7.7% speed increase after installing a separated lane (Kassim et al., 2019). However, Bernardi and Rupi (2015) found slower speeds on separated lanes than on the adjacent motorised lanes due to pedestrian interference. Similarly, Yan et al. (2024) found that cycling was faster on bicycle streets than on separated lanes. Bicycle streets have lower cyclist volume, provide more space, give cyclists priority and restrict the speed of motorised vehicles to 30 km/h (Rivera Olsson & Elldér, 2023).

Bicycle infrastructure design includes five aspects: surface, width, curvature, road segment length and continuity. Poor pavement, such as stone surfaces, reduces safety and comfort, decreasing cycling speed (Manum et al., 2017; Schuhmacher et al., 2025; Toljic et al., 2021; Waintrub et al., 2016). The width of bike lanes influences bicycles' manoeuvrability and interactions between cyclists. Narrow lanes cause frequent braking and frequent steering (Garcia et al., 2015), and more speed changes during interactions, such as overtaking (Li et al., 2019). Therefore, a wider lane results in a higher cycling speed (Boufous et al., 2018). The road curvature also affects safety and manoeuvrability, with curved roads decreasing cycling speed (Arnesen et al., 2019; Belikhov et al., 2025). Longer road segments allow continuous free-flow cycling and reduce frequent deceleration and acceleration at intersections, increasing cycling speed (El-Geneidy et al., 2007; Manum et al., 2017; Strauss & Miranda-Moreno, 2017). Moreover, the discontinuity of bicycle infrastructure, such as the change in bicycle lane types, disturbs smooth cycling and lowers cycling speed (Nabavi Niaki et al., 2018; Waintrub et al., 2016). In summary, straight and wide roads with smooth surfaces, long road segments and continuous infrastructure enable higher speeds.

Road gradients strongly affect cycling speed; in general, downhill roads increase speed, while uphill roads reduce it (Belikhov et al., 2025; Eriksson et al., 2019; Ryeng et al., 2016). For the same gradient, the negative effect of uphill is stronger than the positive effect of downhill (Clarry et al., 2019), since cyclists brake during the downhill for safety. This effect is more evident for steeper downhill roads, where cyclists often stop accelerating and begin decelerating (Flügel et al., 2017; Parkin & Rotheram, 2010; Romero et al., 2015). In predominantly flat places with bridges as the major source of slopes, such as the Netherlands, cycling downhill is slower than on flat roads, as cyclists start the descent at a reduced speed after bridge climbs (Jafari et al., 2025; Yan et al., 2024).

Land use influences cycling speed through factors such as population density, traffic situations and bicycle infrastructure. Compared to built-up areas, green areas (Berjisian & Bigazzi, 2025; Yan et al., 2024) or forest areas (Schuhmacher et al., 2025) facilitate fast cycling due to fewer intersections, turns, and less traffic. Similarly, cycling is slower in city centres than in rural areas or the outskirts (Flügel et al., 2017; Gustafsson & Archer, 2013; Jafari et al., 2025; Schantz, 2017).

Regarding factors at specific locations, cycling through intersections and stop signs involves safety concerns and regulations; therefore, cyclists often decelerate or even stop (Clarry et al., 2019; Romanillos & Gutiérrez, 2019; Strauss & Miranda-Moreno, 2017). Signalised intersections delay cyclists the most, followed by non-signalised intersections and roundabouts (Yan et al., 2024). However, cyclists have higher speeds during green lights than the average and are even faster during yellow lights (Kassim et al., 2017). Four-leg (X-shape) intersections have a stronger effect than three-leg (T-shape) intersections (Flügel et al., 2017). Turns lower cycling speed for the same reason, and left turns have a greater negative effect than right turns in the Netherlands (Yan et al., 2024).

The traffic situation can be simply understood as the presence and movement of road users, including pedestrians, cyclists, and motorised vehicles. Its influence on cycling speed has been less studied. Bernardi and Rupi (2015) observed a lower cycling speed when cyclists are interrupted by pedestrians. During passing situations, cyclists tend to speed up if their speed only slightly exceeds that of the passed cyclists (Khan & Raksuntorn, 2001). Motorised vehicles can cause safety concerns for cyclists and decrease cycling speed at intersections (Kassim et al., 2017). However, Berjisian and Bigazzi (2025) found that cycling speeds are higher on mixed-use roads with high vehicle volume.

Cycling is an active and weather-exposed transport mode (Heinen et al., 2011). Its speed is influenced by weather through safety concerns, physical comfort, and resistance experienced by cyclists. Snow and snowy surfaces cause slippery conditions, thereby prompting cyclists to slow down for better control over their bicycle movement (Shoman et al., 2023). Rain makes skin and clothes wet, decreasing apparent temperature and restricting movement, so cyclists increase their speeds during rainy conditions to reduce the exposure (Maurer et al., 2025; Yan et al., 2024). However, Romanillos and Gutiérrez (2019) found lower speeds in rainy situations. Temperature affects people’s heat balance and muscle performance, and warm weather increases cycling speed compared to cold and hot weather (Strauss & Miranda-Moreno, 2017). Wind alters resistance during cycling: headwinds decrease speed, and tailwinds increase speed (Yan et al., 2024). However, cyclists compensate for the influence of headwinds by increasing their power output (Belikhov et al., 2025), so light winds do not influence speed (Pérez Castro et al., 2025).

2.2.3 Individual characteristics and cycling speed (Arrow 1)

Sociodemographics strongly influence cycling speed, with gender and age being the most frequently examined factors. Most studies found that men cycle faster than women (El-Geneidy et al., 2007; Lin et al., 2008; Stigell & Schantz, 2015; Vlakveld et al., 2015), although some studies did not find gender differences (Parkin & Rotheram, 2010; Yan et al., 2024). Physical strength and social norms are assumed to be the major causes of this speed difference (Stigell & Schantz, 2015). For the same reason, cycling speed decreases with age among adults (Boufous et al., 2018; Schleinitz et al., 2018; Strauss & Miranda-Moreno, 2017).

Few studies examine the influence of physical conditions. Maurer et al. (2025) found that cyclists with higher BMI cycle slower, while Yan et al. (2024) found no influence of self-evaluated health conditions.

Preferences and attitudes significantly influence travel behaviour (De Vos, 2022; Van De Coevering et al., 2021). Their effects on cycling speed, however, have hardly been examined; Yan et al. (2024) found a positive effect of high-speed preference and a negative effect of safety concerns.

Previous cycling experiences, on the one hand, relate to physical conditions and, on the other hand, affect cyclists' preferences and attitudes towards speed. Experienced cyclists tend to have good physical abilities and cycle faster; for example, frequent cyclists (Berjisian & Bigazzi, 2025; Poliziani et al., 2022) and cyclists with winter cycling experience (Strauss & Miranda-Moreno, 2017) have a higher speed. Positive experiences with faster cycling encourage the use of faster bicycles, and thus higher speeds (Fyhri & Fearnley, 2015).

2.2.4 Context and individual characteristics and trip choices (Arrow 2)

The context and individual characteristics indirectly influence cycling speed via other trip choices. Here, we discuss mainly route choice and bicycle choice. Cycling route choices have been well studied, with both revealed preference data (Sener et al., 2009) and stated preference data (Stinson & Bhat, 2003). Cyclists choose the route that provides them with the highest utility, which encompasses a wide range of considerations, including travel time, trip distance, safety, and satisfaction (Liu et al., 2025; Menghini et al., 2010). In general, cyclists prefer short routes with separated bicycle lanes, good surfaces, fewer turns, intersections and slopes, as well as roads with low vehicle volume and speed limits (Łukawska, 2024). The continuity of bicycle infrastructure is also appealing (Segadilha & Sanches, 2014). However, the evaluation of maximum utility differs among cyclists, depending on their gender, age, and experience. For example, senior cyclists are less sensitive to travel time but dislike major arterials due to their high safety concerns (Stinson & Bhat, 2003). Commuters, on the contrary, are more sensitive to travel time than non-commuters and are willing to use the shorter route even with more turns and intersections (Broach et al., 2012). Other contextual factors, such as weather, also influence route choice. We refer to Łukawska (2024) for a more detailed discussion.

Most mode choice studies regard different bicycles as a single type compared to public transport and private cars (Ton et al., 2019). A few studies have examined the choice between different bicycle types and found that the choice of electric and conventional bicycles depends on distinct factors (Campbell et al., 2016). Electric bicycles provide pedal assistance, so they are preferred in situations requiring more physical effort, such as bad weather conditions and air pollution (Campbell et al., 2016). Similarly, people who face physical and health constraints, such as senior adults, tend to choose electric bicycles more often (Johnson & Rose, 2015; Leger et al., 2019; Melia & Bartle, 2021). However, two studies using Chinese datasets found a bell-shaped effect of age on the choice of shared electric bicycles (Campbell et al., 2016) and their own electric bicycles (Cherry & Cervero, 2007), assuming that senior people are reluctant to adopt new things. Furthermore, cyclists who make frequent or long trips are more likely to choose electric bicycles for higher speeds (Campbell et al., 2016; Cherry & Cervero, 2007; Van der Salm et al., 2022). The physical environment of travellers' residential and working locations can also influence the choice of bicycles, but this has hardly been studied.

2.2.5 Trip choices and cycling speed (Arrow 3)

Trip purposes are related to time constraints and traffic conditions. Commuters normally cycle fast (Eriksson et al., 2019; Flügel et al., 2017; Strauss & Miranda-Moreno, 2017), and cycling for exercise is even faster (Romanillos & Gutiérrez, 2019).

Departure time is related to travel purposes; in the morning, during rush hours, and on weekdays, cyclists are more likely to commute and therefore ride faster (Boufous et al., 2018; Clarry et al., 2019; Jensen et al., 2010). Cycling at night is slower because poor lighting conditions raise safety concerns (Strauss & Miranda-Moreno, 2017).

The bicycle, selected for a trip, significantly influences cycling speed (Clarry et al., 2019; Yan et al., 2024). Bicycle classification and standards differ across regions. In Europe, distinction is made by law between conventional electric bicycles and speed pedelecs, which assist pedalling up to 25 km/h and 45 km/h, respectively, while in China, all electric-powered two-wheelers, including electric mopeds, are regarded as electric bicycles (Fishman & Cherry, 2015). Regardless of the classification, cycling with electric bicycles is faster than with city bicycles (Flügel et al., 2017; Jin et al., 2017; Langford et al., 2015; Lin et al., 2008), and speed pedelecs ride even faster (Schleinitz et al., 2017; Twisk et al., 2021). Sporty bicycles are also faster than conventional electric bicycles (Yan et al., 2024). Besides speed itself, trips made by electric bicycles have more and stronger acceleration/deceleration than those of city bicycles (Mohamed & Bigazzi, 2019).

Route choice determines the context of the trip. The influence of bicycle infrastructure and land use was discussed in Section 2.2.2, and here, we focus on trip distance. Longer trips generally have higher cycling speeds (Clarry et al., 2019; El-Geneidy et al., 2007; Lopez et al., 2017; Schantz, 2017), often because they involve commuting and sports purposes, experienced and fit cyclists, better bicycles, and less dense areas (Schleinitz et al., 2018). However, this positive effect flattens out for long trips, such as 15 km (Schantz, 2017).

Speed is also influenced by activities during the ride, especially phone use. Cyclists slow down significantly when answering or using cell phones while cycling (De Waard et al., 2011; De Waard et al., 2014; Kircher et al., 2015). The influence of listening to music on cycling speed is inconsistent, being slightly positive (Kircher et al., 2015) or no effect (De Waard et al., 2011).

2.2.6 The effects of cycling speed (Arrow 4)

Cycling speed affects individuals' accessibility, safety, health, and well-being. Regarding accessibility, increased cycling speeds decrease travel time, enabling cyclists to reach their destinations more quickly (Romanillos & Gutiérrez, 2019). Higher speeds also expand the area that a cyclist can reach within a given time, creating more opportunities to access various services and activities, as demonstrated for electric bicycles (Chondrogianni et al., 2023).

Regarding safety, the existing literature primarily focuses on single-bicycle and bicycle-car crashes. Of all bicycle-related injuries, a significant proportion, ranging from 52% to 85%, depending on the area, does not involve other vehicles (Utriainen et al., 2022). Cycling speed is positively related to the probability of single-bicycle crashes, such as skidding or losing balance when crossing obstacles at excessive speed (Billot-Grasset et al., 2016). It also increases injury severity (Myhrmann et al., 2021); for example, cycling for exercise is more likely to cause severe injuries (Eriksson et al., 2022). However, a lower speed does not always benefit safety, as a certain speed, e.g., at least 12 km/h (Schwab et al., 2012), is needed to keep the balance of bicycles. Some senior people also perceive electric bicycles as more stable and safer than city bicycles (Johnson & Rose, 2015). In addition to the speed itself, heavy brake-related speed decreases can lead to control loss and crashes over the handlebars (Schepers & Wolt, 2012).

For bicycle-car crashes, the impact speed is the most influential factor regarding injuries (Woering et al., 2021). During head-on collisions, a higher cycling speed increases the impact speed and therefore the risk of injury. In addition, a higher speed reduces the time for both drivers and cyclists to take action to avoid collisions, and therefore increases the accident possibility (Schepers et al., 2017).

Cycling benefits health, but the extent of this benefit depends on cycling speed (Van Wee & Ettema, 2016). Higher speeds increase physical activity intensity and improve physical fitness. Speed also influences total air pollutant intake: faster cycling increases breathing rate and volume but shortens exposure duration, making the overall impact uncertain (Bigazzi & Figliozzi, 2014). Some evidence suggests that a higher speed can reduce the total intake of certain pollutants over a fixed travel distance, such as volatile organic compounds (McNabola et al., 2007).

Speed influences well-being. Travellers appreciate the reduction in travel time variability, and unpredictable travel times, especially for commuting, lead to stress and dissatisfaction (Carrion & Levinson, 2013). Therefore, it can be expected that travelling at the expected speed increases cyclists' satisfaction. This tends to be more important for electric bicycle riders, who choose electric bicycles due to a stable and competitive speed (Willis et al., 2013). For example, electric bicycle riders prefer cycling in rural areas, where they can take advantage of electric bicycles, rather than city centres (Plazier et al., 2017). In addition, unstable cycling speed during a trip decreases satisfaction (Joo et al., 2015), as frequent speed adjustments require extra physical and mental effort.

2.2.7 The shape of individual characteristics (Arrow 5)

The aforementioned effects further influence individual characteristics, including preferences, attitudes, physical conditions and bicycle ownership, mainly due to long-term cycling experience. Preferences and attitudes are not stable but subject to change over time (De Vos, 2022). When travellers gain positive experiences about an activity, they tend to develop positive attitudes towards it (Van Wee et al., 2019). For example, people often recognise the benefit of electric bicycles and increase their usage after experiencing the higher speed with less effort (Fyhri & Fearnley, 2015). Similarly, adverse experience contributes to negative attitudes. Lee et al. (2015) found that experiencing injuries during bicycle crashes weakens the attitude toward cycling, and this influence increases with the severity of injuries. Some studies even found that the influence of environment/behaviour on attitudes is more pronounced than the opposite (Kroesen et al., 2017; Van De Coevering et al., 2021). In summary, cyclists who have had positive experiences with high speeds, such as short travel times, improved physical strength, and increased travel satisfaction, tend to have positive attitudes towards speed. Conversely, some negative experiences, like bicycle accidents caused by speeding, may make them more cautious about cycling and high speeds.

These effects' influence on physical conditions is evident; accidents temporarily or permanently worsen physical conditions, depending on the injury severity (Myhrmann et al., 2021), while cumulative health benefits increase overall physical conditions, including better fitness level, lower risks of diseases and being overweight, and longer life expectancy (Oja et al., 2011).

These changes in attitudes and physical conditions lead to shifts in bicycle ownership. When cyclists develop a positive attitude towards speed or gain health benefits from faster cycling, they are likely to purchase and use faster bicycles (Simsekoglu & Klöckner, 2019). Otherwise, they tend to choose slow bicycles or even quit cycling.

2.2.8 Moderation effects (Arrows m1-m3)

Whereas variables have direct effects, they also moderate relationships.

First, the effects of trip choices on speed vary, depending on individual characteristics and contextual situations (Arrow m1). The most studied topic is that the speed advantage of electric bicycles differs across cyclists (Flügel et al., 2017). Cyclists using electric bicycles for less physical effort tend to experience smaller speed increases than those aiming to ride faster. For example, middle-aged adults gain more speed from electric bicycles than senior adults (Schleinitz et al., 2017). Risk-taking behaviour and the design speed of bicycles also play a role. For middle-aged adults, conventional electric bicycles reduce the gender speed gap from 13.0% on city bicycles to 4.9% (Flügel et al., 2017); because they generally prefer relatively high speeds, and the pedal-assist limit of 25 km/h constrains men's speed increase more than women's. However, the gender speed gap expands speed pedelecs (Twisk et al., 2021), as men's higher risk tolerance enables them to utilise the high speed of speed pedelecs. Two earlier studies from China found a similar result that electric bicycles enlarge the speed difference between genders (Jin et al., 2017; Lin et al., 2008), since electric bicycles are not limited by speed or power output.

Another moderating effect is that the influence of the chosen route on cycling speed varies across cyclists and bicycles. In places where stops and deceleration are involved, such as red lights and turns, faster cyclists and bicycles are delayed more (Kircher et al., 2018; Maurer et al., 2025; Yan et al., 2024). For example, the speed differences between city bikes and race bikes decrease on rougher surfaces (Toljic et al., 2021) and are smaller in urban areas than in rural areas (Twisk et al., 2021). In contrast, stronger cyclists and faster bicycles slow down less during situations requiring extra effort, such as cycling uphill (Flügel et al., 2017).

Second, the influence of cycling speed on its effects is moderated by trip choices, such as bicycle types (Arrow m2). Regarding health, electric bicycles offer pedal assist, allowing riders to maintain the same speed with a lower intensity of physical activity than city bike riders (Bourne et al., 2018). Langford et al. (2017) observed that e-bike users expend 24% less energy for the same trip. This reduced exertion at a given speed also implies potentially lower intake of air pollutants. Regarding safety, e-bike riders have similar safety behaviour to city bicycle riders, such as wrong-way cycling (Langford et al., 2015), but the same speed can lead to higher safety risks for e-bike users, especially seniors, because the greater bicycle weight makes balancing more difficult (Haustein & Møller, 2016). In addition, considering that some people choose electric bicycles for high speeds (Cherry & Cervero, 2007), e-bike riders are expected to be more dissatisfied compared to city bike riders when encountering speed losses to the same extent.

The physical environment and traffic conditions of the chosen routes also moderate the relationship between speed and its effects, but there is less available evidence. Regarding health, pollutants distribute unevenly across places; compared to roads with less traffic, busy roads have a higher concentration of pollutants (Jarjour et al., 2013; Wesseling et al., 2021). Therefore, with the same cycling speed, busy roads can lead to higher intakes of air pollutants. Regarding safety, complicated situations, such as rough surfaces, bad weather and busy traffic, create more obstacles and reduce the space for cyclists to avoid potential accidents, therefore amplifying the influence of cycling speed on safety. For example, many single-bicycle crashes are related to road works, which cause severe injuries (Niska et al., 2022).

The third moderation effect is that individual characteristics, such as physical conditions, moderate the effects of cycling speed (Arrow m3). The health benefits of a specific exercise workload decrease with people's basic fitness levels (Celis-Morales et al., 2017), which means that less fit cyclists benefit more from the same cycling speed than strong cyclists. Other moderation effects are conceptually plausible; for example, cyclists with respiratory diseases may be more negatively influenced by air pollution when cycling at the same speed as healthy cyclists. However, these potential moderation effects remain untested.

2.2.9 Bidirectional relationships

Individual characteristics and the context influence each other (Arrow b1), with the development of attitudes and residential self-selection as two core components. Without considering this bidirectional relationship, research may encounter problems with reverse causality. People develop their attitudes towards cycling based on the mobility culture, physical environment and traffic situations around them (Hudde, 2023; Van De Coevering et al., 2016). In places with good bicycle infrastructure, people tend to have a positive attitude towards bicycle purchase (Zhao et al., 2018). Second, people proactively choose residences that match their cycling-related attitudes, a phenomenon known as residential self-selection (Bohte et al., 2009; Cao et al., 2009). Ignoring the residential self-selection regarding cycling speed may lead to the incorrect allocation of the influence of attitudes on physical environment and traffic situations. However, cycling speed-related attitude development and residential self-selection have hardly been studied (Van Wee et al., 2019).

Different trip choices also influence each other (the block of Trip choices). Here, we take the relationship between bicycle choice and route choice as an example. Electric bicycles and city bicycles differ in effort requirement, and people choose specific routes for their bicycles. For example, compared to city bicycle riders, e-bike riders are less concerned with hills and the existence of separated bicycle lanes along routes (Khavarian et al., 2024; Meister et al., 2023).

In addition, e-bike riders may avoid urban areas, as they lose the speed advantage of electric bicycles (Plazier et al., 2017). In reverse, it is also possible that people choose the specific type of bicycle based on route conditions. For instance, for a grocery shopping trip within a small city, people may choose city bicycles instead of electric bicycles due to short distances, high bicycle volume, and unsafe bicycle parking. The bidirectional relationships between different cycling choices exist but are hardly studied.

2.3 Findings and Discussion

Cycling speed is a complex phenomenon, being embedded in a feedback loop. Contextual and individual characteristics influence cycling speed directly and indirectly through trip choices. Speed affects individuals' accessibility, health, safety and well-being, which in turn change their physical condition and attitudes. These changes subsequently shape future cycling behaviour. Beyond this feedback loop, additional complexity arises from moderation and bidirectional relationships. Accounting for these complex factors and relationships can provide more detailed and accurate insights into how cycling speed is determined. Ignoring them, such as cyclists' residential self-selection based on their preferences and attitudes, may lead to biased results, including overestimating the effect of bicycle infrastructure on speeds. Most existing studies, however, focus mainly on the direct effects of certain determinants on speed and pay relatively little attention to other complicated relationships. Especially, the reinforcement and weakening of speed-related attitudes due to the effects of speed, the subsequent effects of these attitudes on speed, and the moderating effects whereby the speed of cyclists and bicycles is influenced differently by the same determinants remain largely unexplored.

Cycling speed varies continuously during a ride. Existing literature on individual speeds typically examines either average speeds (e.g., Schleinitz et al., 2018) or spatial variations by identifying locations where speeds are relatively high or low (e.g., Arnesen et al., 2019). However, longitudinal speed variation, namely how speed changes over time within a ride, such as speed increases and decreases, has received far less attention. Berjisian and Bigazzi (2025) explored longitudinal speed measurement, focusing only on cruising segments, where speeds remain relatively stable.

Existing studies have investigated various factors that influence cycling speed. The underlying mechanisms are typically assumed to relate to cyclists' physical and mental conditions (e.g., age and gender), preferences, required physical effort (e.g., bicycle types, wind and slope), safety or regulatory conditions (e.g., turns and intersections), interactions with others (e.g., bike lane types, overtaking and the existence of pedestrians) and comfort (e.g., pavement, temperature and rain). However, the observed effect of any given factor is often driven by multiple underlying mechanisms operating simultaneously. For example, headwinds increase resistance, but cyclists compensate by exerting extra effort, especially under light-wind conditions (Belikhov et al., 2025). For many factors, the exploration of underlying causal mechanisms remains insufficient.

Understanding the mechanisms behind cycling speed is crucial for developing place-specific policies targeting speeds. Inconsistent findings on the influence of bicycle lane types highlight this importance. Many studies have found higher speeds on physically separated bike paths (e.g., Clarry et al., 2019; Flügel et al., 2017), attributing this to reduced disturbance from motorised vehicles. However, Bernardi and Rupi (2015) found the opposite because separated paths are narrow and sometimes occupied by pedestrians. Conversely, cyclists can maintain higher speeds on a dedicated bus lane where they experience fewer interruptions. Similarly, Yan et al. (2024) observed lower speeds on physically separated paths compared to bicycle streets, attributing this to frequent interactions among cyclists on separated paths. These examples suggest that the speeds on different bike lanes depend on regulation (e.g., permitted road users, priority rules, motor-vehicle speed limits), demand (cyclist density) and supply (path width). These aspects, however, vary substantially from place to place. Thus, identical infrastructure can yield different outcomes, reinforcing the need for context-specific policies informed by these mechanisms.

2.4 A Research Agenda

As the conceptual model (Figure 2.1) illustrates, cycling speed is part of a feedback loop that involves various factors, complex relationships, and a decision-making process. However, most existing studies focus on the direct relationships (Arrows 1 and 3). The ignorance of these complex relationships can lead to biased results, such as overestimating the effect of bicycle infrastructure on speeds due to overlooking self-selection. Therefore, the main recommendation is to consider these relationships or, at the very least, be aware of the complex conceptual model in empirical studies. We list the most important topics that help explore speed but have largely been neglected in existing studies.

The first topic is exploring cyclists' perspectives on cycling speed (the block of Individual characteristics in Figure 2.1). The conceptual model links cycling speed to accessibility, safety, health and well-being, which further shape individuals' speed-related attitudes. However, the extent to which cyclists notice and consider these effects remains unclear. The level of awareness is essential for assessing the relevance of speed-focused research and interventions. In addition, understanding perspectives helps to explore the mechanisms behind cycling speed choices. The perspectives include: (1) the importance of cycling speed, (2) the importance of its various effects, and (3) other factors considered in cycling speed choices.

Second, longitudinal measured speed changes within a ride (the block of Cycling speed in Figure 2.1) remain largely unexplored (Yan et al., 2026). Speed stability benefits cyclists by increasing overall speeds (Berjisian & Bigazzi, 2025), reducing travel time (Strauss & Miranda-Moreno, 2017), lowering the risk of crashes, decreasing the required physical effort, and improving travel satisfaction (Joo et al., 2015). We, therefore, recommend studying cycling speed stability, including its definition, measurement, degree within trips, and determinants.

Third, beyond the physical environment, we recommend examining other contextual factors, including mobility culture, weather, and traffic conditions (the block of Context in Figure 2.1). The mobility culture encompasses both the intangible dimension, such as social norms, and the tangible dimension, like bicycle infrastructure (Stolze et al., 2025), which are interrelated. Individuals within a region often share similar behaviours and mindsets. Exploring mobility culture could help to explain regional differences in cycling speed. Weather and traffic situations change over time, causing cycling speed to vary for the same route. These conditions reduce travel time reliability and influence the attractiveness of cycling. However, these aspects remain largely underexplored.

The fourth topic concerns joint trip choices and their impact on cycling speed (Arrow 3 in Figure 2.1). Cycling speed is influenced by multiple interrelated trip choices, such as bicycle mode and route. For example, people using electric bicycles may choose routes outside cities for a smoother ride. Most existing studies, however, only consider the outcomes of these choices, such as bicycle types and route conditions. Ignoring the decision-making process, especially the joint travel decision, these studies are prone to endogeneity problems and cannot disentangle the effects of different trip choices. Research that incorporates all travel decisions is challenging due to data and methodological requirements, and beginning with two choices simultaneously, such as bicycle choice and route choice, would be beneficial.

The fifth topic is the effects of cycling speed and their potential to shape attitudes towards cycling speed (Arrows 4 and 5 in Figure 2.1). Increasing evidence shows that individuals' attitudes can be shaped by their behaviour (Van Wee et al., 2019). This also applies to cycling speed: the consequences of cycling at different speeds may reinforce or alter cyclists' speed-related attitudes. Although some studies have examined certain effects of cycling speed, such as safety (Schepers et al., 2017) and pollution intake (McNabola et al., 2007), little is known about how these effects shape attitudes and preferences. Therefore, examining arrows 4 and 5 separately, and especially jointly, is recommended.

Sixth, empirical analysis regarding cycling speed-related self-selection is rare (Arrow b1 in Figure 2.1). Self-selection is widely recognised in travel behaviour studies (Cao et al., 2009) and may confound the relationship between the targeted determinants and travel behaviour. This also applies to cycling speed; cyclists may select residential locations, bicycle types, and cycling routes based on their speed-related attitudes. To obtain precise and unbiased results, further investigation into this topic is needed.

Seventh, moderation effects require more exploration (Arrows m1-m3). The influence of certain determinants, such as bicycle types, on cycling speed is not uniform but moderated by the characteristics of cyclists and the physical environment. For example, faster cyclists are delayed more by intersections (Yan et al., 2024). Such moderation partially reflects cyclist and geographic heterogeneity in cycling speed. Understanding cyclist heterogeneity is essential for identifying the specific challenges faced by different groups and for developing targeted policies. Likewise, examining geographic heterogeneity can reveal the shape of local spatial attributes on cycling behaviour and design place-based interventions to support cycling.

The eighth topic is applying suitable analysis methods. The complex causal structure of cycling speed requires correspondingly advanced statistical models, such as structural equation models and multilevel models. In addition, a dynamic reinforcement between cycling speed and attitude is assumed, so longitudinal data and related analysis methods are required.

2.5 Conclusion

This study contributes to cycling behaviour research by focusing on cycling speed. A conceptual model is proposed to illustrate the complexity of the process by which cycling speed is determined. Speed is not only embedded in a feedback loop but also involves moderation effects and interrelationships.

The review reveals that most existing studies examine direct effects of specific factors, such as bicycle types, while a comprehensive understanding of a broader set of determinants and relationships remains limited. In particular, gaps persist regarding cyclists' perspectives on cycling speed, joint travel decisions and their influence on cycling speed, the shape of speed-related attitudes, speed-related self-selection, factors that change over time, and longitudinal speed stability within a ride. Correspondingly, richer data, such as longitudinal data, and advanced methods, like structural equation models, are required.

Based on these insights, the empirical chapters of this thesis will comprehensively investigate speed variation and speed stability within rides. They will examine a wide range of determinants, account for cyclist and geographic heterogeneity, and estimate multilevel models that can handle complex interdependencies.

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Chapter 3: Examining the Determinants of Cycling Speed: A Review of Empirical Study Designs

3.1 Introduction

The importance of cycling speed in practice and in empirical research has been increasingly recognised. Speed is related to the competitiveness and attractiveness of cycling. Higher speeds increase cycling accessibility by reducing travel time and expanding the number of opportunities to reach various activities (Geurs & van Wee, 2004). Since travel time is often perceived as a disutility, especially for commuting trips (Koster & Koster, 2015), travellers tend to choose transport modes and routes with shorter travel times (Frank et al., 2007; Liu et al., 2025; Sener et al., 2009). Cycling speed is also related to individuals' health (De Geus et al., 2007), trip satisfaction (Joo et al., 2015), and safety (Schepers et al., 2017). Furthermore, understanding speed and its variations within a trip is necessary for accurate cycling modelling (Castro et al., 2022; Flügel et al., 2017; Romanillos & Gutiérrez, 2019), such as bicycle congestion models (Paulsen & Nagel, 2019). Therefore, an increasing number of studies have examined the determinants of cycling speed (Clarry et al., 2019; El-Geneidy et al., 2007; Pérez Castro et al., 2025; Yan et al., 2024).

Accurately examining the determinants of cycling speed depends on the study design employed, and existing studies exhibit substantial heterogeneity in this regard. For example, cycling speed has been measured as aggregated speed at specific locations (Jin et al., 2017), as an average over a trip (Schleinitz et al., 2017) or over a trip segment (El-Geneidy et al., 2007), and as instantaneous speeds at locations along a route (Arnesen et al., 2019). However, the respective advantages and disadvantages of different study designs remain insufficiently synthesised. Such insight is necessary for evaluating existing studies and for supporting future research in choosing appropriate study designs.

Therefore, this chapter aims to systematically review empirical study designs used to examine the determinants of cycling speed. It focuses on data collection strategies, speed measurement strategies, examined determinants, and analytical approaches. The review covers studies in the transportation domain, including both commuting and leisure cycling, which consider the relationship between the environment and speed. Studies in other domains, such as professional sports, are excluded. In addition, only empirical studies with cycling speed as a primary research topic are included, as they provide sufficient methodological details relevant to speed analysis.

The studies were collected based on the literature search method suggested by Van Wee and Banister (2016). The search was conducted using the Scopus dataset and was limited to English-language articles until September 15, 2025. Three sets of keywords related to cycling (bicycl* OR cycl* OR bik* OR rid*), speed (velocit* OR speed* OR flow* OR pac*), and determinants (environment* OR facilit* OR infrastructure*) were combined for the search. The cycling and speed-related keywords were searched within the article title to ensure that cycling speed is the central topic, while environment-related keywords were searched within the article title, abstract and keywords. In addition, papers in unrelated subject areas, such as chemistry, medicine, and agriculture, and papers without cycling/transportation-related keywords were filtered out. This initial search found 101 articles. Their title and abstract were then manually reviewed, and 18 papers met the criteria. Finally, the full text of these papers was reviewed, and 16 additional papers were identified through forward and backward snowballing, resulting in a total of 34 papers.

The following section summarises and classifies empirical study designs used in existing literature, followed by evaluations of these designs and relevant recommendations in Section 3.3. The conclusion is presented in Section 3.4.

3.2 Classification of Empirical Study Designs

In total, 34 papers that empirically examined the determinants of cycling speed are included in this review. These studies are classified into three categories of empirical study designs, distinguished by their data collection strategies. Targeted-segment-based studies collect naturalistic cycling data at specific road segments. Experiment-based studies recruit cyclists and ask them to cycle along predefined routes under controlled or targeted conditions. Whole-trip-based studies focus on daily cycling and collect cycling speed over entire trips. These study designs differ systematically in their data collection techniques, speed measurement, study units, the determinants that can be examined, and analytical approaches.

The remainder of this section first summarises all included papers, then describes cycling data collection techniques, and finally discusses three study designs.

3.2.1 Summary of papers

The first research was conducted in 1980 (Opiela et al., 1980), and most studies on this topic have emerged since 2015 (Table 3.1). Most studies (n = 20) were from Europe, six focused on North America, and five were from China. Eleven studies used cycling data from targeted

Table 3.1: Classification of papers based on their study designs

Categories	Study unit	Reference	Place	Data collection techniques	Samples	Analytical approaches	Aim of the study
Targeted-segment-based studies (n = 11)	Segment	Lin et al. (2008)	Kunming, China. 8 road segments	Cameras along roads	3,022 observations	Descriptive analysis	Bicycle types, Bicycle flow
		Jin et al. (2017)	Hangzhou, China. 11 road segments	Cameras along roads	39,820 observations aggregated into 566 samples	Linear regression	
		Li et al. (2019)	Nanjing, China. 4 road segments	Cameras along roads	Not given	Descriptive analysis	
		Yan et al. (2020)	Nanjing, China. 6 road segments	Cameras along roads	1,370 observations	Linear regression	
		Boufous et al. (2018)	Sydney, Australia. 12 road segments	Cameras along roads	5,421 observations	Logistic regression	Other road users, Bike lane type
		Eriksson et al. (2019)	Eskilstuna, Linkoping and Stockholm, Sweden. 20 road segments	Cameras along roads, Rubber tubes, MetreCount	4,604 observations	Descriptive analysis	

		Opiela et al. (1980)	Michigan, USA. 15 intersections	Cameras along roads	159 observations	Descriptive analysis	Cycling at intersections
		Waintrub et al. (2016)	Santiago, Chile. 7 intersections	Cameras along roads	1,828 observations	Linear regression	
		Kassim et al. (2017)	Ottawa, Canada. 3 intersections	Cameras along roads	523 observations	Linear regression	
		Toljic et al. (2021)	Vienna, Austria. 7 road segments	Radar gun	3,750 observations	Descriptive analysis	Road surface
		Ye and Chen (2013)	Nanjing, China. 5 road segments	Cameras along roads	5,938 e-bikes and 3,377 city bikes aggregated into 478 samples	A hazard-based duration modelling	Curb-side parking
Experiment-based studies (n = 5)	Segment	Kircher et al. (2015)	Sweden. A designated	GPS devices, Cameras on	21 cyclists, 5 trips each	Descriptive analysis	Cell phone use
		Vlakveld et al. (2015)	The Hague, the Netherlands. A designated route	GPS, Speedometer, Rotation sensor, Camera	58 cyclists	Descriptive analysis	Cyclist characteristics
		Kircher et al. (2018)	Linköping, Sweden. A designated route	GPS devices, Cameras	41 cyclists, 2 trips each cyclist	Descriptive analysis	

		Bernardi and Rupi (2015)	Bologna, Italy. 3 road segments	Manually observing, Cameras	One cyclist rides 100 times at each segment	Descriptive analysis	Other road users, Bike lane type
		Belikhov et al. (2025)	Linköping, Sweden; Wuppertal, Germany	GPS device, Speed meters	57 cyclists, 57 trips	Multilevel model	Free riding behaviour
Whole-trip-based studies (n = 18)	Trip	Jensen et al. (2010)	Lyon, France	Sharing bicycle system	11.6 million trips	Descriptive analysis	
		Schantz (2017)	Stockholm, Sweden	Self-reported	1,661 cyclists	Linear regression	
		Schleinitz et al. (2018)	Chemnitz, Germany	GPS device, Cameras on bicycles	76 cyclists, 3,416 trips	Multilevel model	
		Twisk et al. (2021)	The Hague, the Netherlands	GPS device	46 cyclists, 832 trips	Multilevel model	
	Segment	El-Geneidy et al. (2007)	Minneapolis, USA	GPS device	8 cyclists	Linear regression	
		Parkin and Rotheram (2010)	Leeds, UK.	GPS device	16 cyclists, 518 trips	Linear regression	
		Manum et al. (2017)	Gothenburg, Norway	Smartphone app	15 cyclists	Linear regression	
		Schleinitz et al. (2017)	Chemnitz, Germany	GPS device, Cameras on bicycles	85 cyclists, 4,327 trips	Descriptive analysis	

		Strauss and Miranda-Moreno (2017)	Montreal, Canada	Smartphone app	Among 1000 cyclists, more than	Linear regression	
		Flügel et al. (2017)	Oslo, Norway	Smartphone app	709 cyclists, 48,633 trips	Linear regression	
		Romanillos and Gutiérrez (2019)	Madrid, Spain	Smartphone app	328 cyclists, 3,970 trips	Finite Distributed Lag	
		Jafari et al. (2025)	Melbourne, Australia	Smartphone app	31,222 cyclists, 253,424 trips	Linear regression, Random Forest models	
		Schuhmacher et al. (2025)	Hamburg, Germany	Smartphone app	91,083 segments	Gamma regression model	
		Berjisian and Bigazzi (2025)	Vancouver, Canada	Smartphone app	135 cyclists, 1,606 trips	Multilevel model	
		Maurer et al., (2025)	Zurich, Switzerland	Smartphone app	351 cyclists	Extra-Trees Regressor	
	Point	Arnesen et al. (2019)	Trondheim, Norway	Smartphone app	15 cyclists, 2,085 trips	Forward Markov model	
		Clarry et al. (2019)	Toronto, Canada	Smartphone app	554 participants, 5,713 trips	Multilevel model	
		Yan et al. (2024)	The Netherlands	GPS device	60 cyclists, 508 trips	Multilevel model	

segments, five studies conducted experiments, and 18 studies collected and analysed cycling speed over entire trips. Most recent studies adopt a whole-trip-based design.

3.2.2 Data collection techniques

Cycling speed data collection techniques have evolved with technological advancements, from manual estimation and manual observation to automatic collection. These techniques can be used for either fixed-location observation, such as radar guns, tunnel tubes, and cameras along roads, or for measurement of entire rides, including retrospective estimation, standalone GPS devices, smartphone tracking apps, and their combination.

Table 3.2 lists this classification; techniques, illustrated from left to right, become more automatic and capable of collecting more information. The table also links the study designs to different data collection techniques. Typically, targeted-segment-based studies employ fixed-location observation techniques, particularly cameras along roads. Whole-trip-based studies rely on measurement of entire rides, especially through smartphone apps. Experiment-based studies also employ entire-ride measurement but use mixed techniques, such as cameras and GPS devices, to observe detailed behaviours. We refer to Kassim et al. (2020) for more details of these techniques, including their processes, advantages, and limitations.

Table 3.2: Speed collection techniques across three study designs[a]

Fixed location observation				
Techniques	Stopwatches or radar guns	Tunnel tubes	Cameras	
Targeted-segment-based studies	Toljic et al. (2021)	Eriksson et al. (2019)	Boufous et al. (2018) Jin et al. (2017) Opiela et al. (1980)	
Measurement of entire rides				
Techniques	Retrospective estimation	Standalone GPS devices	Smartphone tracking apps	A combination of GPS devices, cameras, and speed sensors
Whole-trip-based studies	Schantz (2017)	El-Geneidy et al. (2007) Yan et al. (2024)	Arnesen et al. (2019) Berjisian and Bigazzi (2025) Romanillos and Gutiérrez (2019)	Schleinitz et al. (2018)
Experiment-based-studies				Belikhov et al. (2025) Kircher et al. (2018) Vlakveld et al. (2015)

[a] This table provides examples instead of listing all studies reviewed in this chapter. Data collection techniques for all studies are presented in Table 3.1.

3.2.3 Targeted-segment-based studies

Targeted-segment-based studies (n = 11) usually begin with a specific research aim, namely, examining particular determinants, such as bicycle types (Lin et al., 2008) and intersections (Kassim et al., 2017). They deploy cameras or tunnel tubes at selected locations to collect cycling data (e.g., Jin et al., 2017; Waintrub et al., 2016). For example, to examine cycling speed across different bicycle lanes, Boufous et al. (2018) collected cycling data using cameras on 12 roads with different bicycle infrastructure. These studies calculate speed by dividing the length of the observation segment by the time that cyclists take to traverse it (Lin et al., 2008; Opiela et al., 1980). They tend to use aggregated speeds at road segments (Yan et al., 2020) or at combinations of road segments and time slots (Jin et al., 2017). Due to on-site observation of naturalistic cycling, they have a relatively big number of observations, depending on bicycle volumes and data collection duration, such as 4,604 observations in Eriksson et al. (2019) and 39,820 observations in Jin et al. (2017). However, cyclist characteristics are hardly available; one exception is Jin et al. (2017), who recognised gender from video footage.

A small number of influential factors examined require relatively straightforward analytical approaches, including descriptive analysis and simple linear regression. For studies that only examine one factor, descriptive analysis is mainly used (e.g., Eriksson et al., 2019; Lin et al., 2008; Vlakveld et al., 2015), while linear regression is primarily estimated by papers with multiple factors (e.g., Jin et al., 2017; Waintrub et al., 2016; Yan et al., 2020).

3.2.4 Experiment-based studies

Five studies employ experimental designs to explore in-ride behaviour, such as phone use, which is difficult to capture through observations of daily cycling. Four of them recruit volunteers to cycle along designated routes (Belikhov et al., 2025; Kircher et al., 2015; Kircher et al., 2018; Vlakveld et al., 2015). GPS devices and cameras are mounted on bicycles to record detailed behaviour and corresponding changes in cycling speed. The complexity of data collection results in a small sample size, ranging from 21 to 58 participants. For example, Kircher et al. (2015) recruited 21 cyclists and examined the influence of cell phone use on cycling speed. Participants were assigned various tasks, including making phone calls, sending text messages, and browsing the web, at designated locations during their cycling. Bernardi and Rupi (2015) adopted a different experimental approach; a researcher repeatedly cycled 100 times at three sites with varied bicycle lane types to examine the influence of bicycle infrastructure and disturbances from other road users on cycling speed.

Regarding study units and analytical approaches, Belikhov et al. (2025) focused on segments where cyclists are unconstrained by other road users and traffic control and defined these segments as free riding. They estimated multilevel models to examine various determinants of free-riding speed, such as wind, slopes, and curves. The other four studies focus on the segments where interventions, such as phone calls and disturbances from other road users, occur. They calculate the average speed on these segments and examine the influence of interventions using descriptive analysis.

3.2.5 Whole-trip-based studies

3.2.5.1 Data collection

Most whole-trip-based studies collect data using GPS devices (e.g., Yan et al., 2024), smartphone tracking apps (e.g., Clarry et al., 2019), or a combination of GPS devices and cameras (Schleinitz et al., 2017). An exception is Schantz (2017), who calculated speed using the travel time estimated by participants and the cycling routes they drew on a map. GPS devices and smartphone apps register a tracking point with temporal and spatial information every several seconds. This allows researchers to (1) recognise the cycling routes, (2) calculate speeds for each point, and (3) link precise spatial and temporal information, such as bicycle infrastructure, land use and weather conditions, to tracking points and trips. Therefore, these studies can investigate speed variation during a ride and test a wide range of factors (e.g., Romanillos & Gutiérrez, 2019). In addition, cyclist characteristics can be collected in these studies; for example, Yan et al. (2024) investigated the effect of cyclists' attitudes on speed, and Schleinitz et al. (2017) examined the influence of age and gender.

However, GPS devices require delivery and collection, involving a high cost, so studies using GPS devices have a relatively small sample size, such as eight participants in El-Geneidy et al. (2007) and 85 cyclists in Schleinitz et al. (2018). Smartphone tracking apps are easily accessible, helping expand the sample size largely (Flügel et al., 2017; Strauss & Miranda-Moreno, 2017).

3.2.5.2 Speed calculations and determinants

Whole-trip-based studies differ in the study units at which speeds are calculated and analysed, including the trip (n = 4), the trip segment (n = 11) and the tracking point (n = 3). Therefore, speed calculation methods also vary. A smaller study unit captures more details in speed variations and allows for the examination of a wider range of determinants, but its speed calculation is more complicated and involves greater measurement errors (Table 3.3).

Table 3.3: Differences in speed measurement and determinants between the three study units of whole-trip-based studies

Study unit	Speed calculation complexity	Speed accuracy	Speed variation captured	Determinants considered
Trip	Low	High	Low	Characteristics of cyclists, bicycles and trips
Segment	High	Medium	Middle	All determinants, except for those that change continuously along the trip
Tracking point	High	Low	High	All determinants

Studies with the trip as the study unit use the average trip speed, which can be easily calculated by dividing the trip length by its duration (Jensen et al., 2010; Schantz, 2017; Schleinitz et al., 2018; Twisk et al., 2021). The trip length is derived from the map-matched route, and the duration is calculated from the time stamps of the first and last tracking points. Since the potential GPS noise of these two tracking points can be largely averaged out over the entire trip, the calculated average trip speed is highly accurate. However, this method does not capture speed changes during trips. In addition, the considered determinants are limited to those being constant for a trip, namely the characteristics of cyclists, bicycles, and trips, such as age, gender, bicycle types (Schleinitz et al., 2018; Twisk et al., 2021), departure time (Jensen et al., 2010), and trip length (Schantz, 2017).

Studies with the segment as the study unit require splitting a trip into segments. Segmentation depends on research aims and varies across studies. It is assumed that the considered physical environment of a segment is largely monotonous, and its cycling speed remains constant throughout the segment. Intersections can cause significant speed fluctuations, so many studies recognise a segment between two intersections (Flügel et al., 2017; Strauss & Miranda-Moreno, 2017). El-Geneidy et al. (2007) identified segments based on the same bicycle infrastructure (on-street lanes, off-street lanes, and mixed-use roads). Manum et al. (2017) considered more factors, including intersections, bicycle infrastructure, slope and curve. Berjisian and Bigazzi (2025) relied on speed profiles to recognise segments which exhibit cruising speeds.

After segmentation, the segment speed is calculated by dividing the segment length by its duration (El-Geneidy et al., 2007; Flügel et al., 2017; Maurer et al., 2025), by averaging speeds over all tracking points of the segment (Strauss & Miranda-Moreno, 2017), or by finding the median speed of all points of the segment (Berjisian & Bigazzi, 2025). In addition, four papers aggregate the speed of all cyclists on a segment (Jafari et al., 2025; Manum et al., 2017; Schuhmacher et al., 2025; Strauss & Miranda-Moreno, 2017).

Compared to the average trip speed, the segment speed keeps more speed information, partially illustrating speed changes within a trip. Correspondingly, it allows the examination of determinants that vary during a trip, such as bicycle infrastructure and intersections (Maurer et al., 2025; Strauss & Miranda-Moreno, 2017). However, the accuracy of the calculated speed is relatively low for two reasons. Using more tracking points to calculate speed increases the likelihood that biased or erroneous GPS points are included. In addition, the short length and duration of trip segments limit the ability to average out GPS errors when biased GPS points are involved. Consequently, data filtering and speed smoothing are often required. For example, Romanillos and Gutiérrez (2019) filtered out segments shorter than 20 metres, while Strauss and Miranda-Moreno (2017) smoothed speed using the speed value of three preceding and following tracking points.

Studies that treat the tracking point as the study unit calculate cycling speed at every point. This speed can closely reflect actual speed variation within a ride. Through spatial information of tracking points, factors related to the physical environment can be measured precisely and linked to these points, including those changing almost continuously during a trip, such as curvature and slope (Arnesen et al., 2019). This speed is often calculated using the distance and duration between two consecutive points (Clarry et al., 2019; Yan et al., 2024). For the same reasons as segment speed, speeds calculated at tracking points are likely to deviate from their actual speeds. Therefore, studies pay extra attention to data noise filtering (Arnesen et al., 2019).

3.2.5.3 Analytical approaches

Due to a wide range of determinants and a complex data structure, whole-trip-based studies often require complicated analysis methods; however, descriptive analysis and linear regression are also widely employed. Two studies use descriptive analysis, since they focus only on the differences in average trip speeds between bicycle types (Schleinitz et al., 2017) and between departure times (Jensen et al., 2010). More studies estimate linear regression (El-Geneidy et al., 2007; Flügel et al., 2017; Schantz, 2017; Strauss & Miranda-Moreno, 2017), and it reveals the extent to which different determinants influence cycling speed. However, this method overlooks that the cycling data structure violates the assumption of independent error terms in linear regression. Most whole-trip-based datasets have a nested structure, where cyclists make multiple trips, and a trip consists of many segments or points. Consequently, the observations are not fully independent. Trips made by a cyclist share common characteristics, such as physical conditions, while segments or points within a trip share trip-level attributes, like bicycle types. Furthermore, the cycling speed at a tracking point is closely related to the speed at its previous point. Therefore, linear regression can lead to misleading results.

To address this issue, some complicated statistical models are estimated. To account for the correlation between continuous observations, Romanillos and Gutiérrez (2019) estimated a finite distributed lag model, and Arnesen et al. (2019) estimated a forward Markov model. Considering the nested data structure, some studies estimated multilevel linear models (Clarry et al., 2019; Schleinitz et al., 2018; Yan et al., 2024), which introduce random intercepts for each group to account for the unobserved group attributes shared by its observations.

3.3 Evaluations and Recommendations

Studies employing three different study designs can all contribute to enhancing the understanding of the determinants of cycling speed, but each has its own advantages and disadvantages. This section discusses these aspects for each of the three categories of empirical study design.

3.3.1 Advantages and disadvantages

3.3.1.1 Targeted-segment-based studies

Targeted-segment-based studies can collect a large amount of data within a relatively short duration, due to the automatic on-site data collection capabilities of cameras. For example, Jin et al. (2017) collected 39,820 observations at eleven sites within 14 days. Additionally, they focus on specific factors and can observe the details of these factors, enabling an in-depth understanding. For example, Kassim et al. (2017) modelled cycling speeds at intersections and considered many details, such as bicycle infrastructure settings, traffic signal indications, presence and movement of vehicles and pedestrians.

Despite these strengths, these studies capture speed information only at their targeted segments. This limits the understanding of speed variation within a ride. In addition, speeds are often measured aggregately, and therefore, detailed speed differences between cyclists and between bicycles cannot be well examined. Furthermore, these studies focus on the specific determinants which can lead to confounding bias.

3.3.1.2 Experiment-based studies

Experiment-based studies can explore in-ride behaviour, including phone use (Kircher et al., 2015) and interactions with other road users (Bernardi & Rupi, 2015). These behaviours occur randomly during daily cycling, making systematic observation difficult. In addition, cameras or on-site researchers are often required to capture these behaviours. By intentionally inducing the targeted behaviours to occur more frequently, experimental studies enable the collection of sufficient observations.

More importantly, through a designed experiment, these studies can reveal mechanisms behind certain influences. Kircher et al. (2015) examined the influence of phone use on cycling speed, distinguishing user-initiated and device-initiated phone use. They found that cyclists decelerate before making calls but decelerate when receiving calls. Similarly, Bernardi and Rupi (2015) examined the relationships between bike lane setting, disturbance of other road users and speed. They found that cycling on physically separated lanes encounters frequent disturbances from pedestrians and moderate speed losses, while disturbances from motorised vehicles on mixed-use lanes are infrequent but result in severe cycling speed reductions.

However, due to difficulties in participant recruitment and the complexity of the experimental procedures, these studies typically have small sample sizes, both in terms of cyclists and the number of trips per cyclist. Such small samples increase the risk of biased results caused by outliers.

3.3.1.3 Whole-trip-based studies

Whole-trip-based studies record speed information of entire trips and can simultaneously examine the influence of a wide range of determinants (Clarry et al., 2019; Maurer et al., 2025; Yan et al., 2024). During a trip, cycling speed varies almost constantly due to changes in both built and natural environments. In addition, at any given moment, cycling speed is influenced by a combination of factors. Studies that use segments or tracking points as the study unit capture speed variation during a trip and can link cycling speed to detailed environmental factors. In addition, the characteristics of cyclists and bicycles can be collected, such as preferences (Yan et al., 2024), BMI (Maurer et al., 2025) and bicycle types (Schleinitz et al., 2017). This enables a comprehensive examination of the determinants that influence cycling speed.

The disadvantages primarily lie in potential GPS errors and the complexity of speed measurement, which can lead to inaccurate speed calculations, particularly when using short study units. Although GPS accuracy remains a concern in some datasets, its influence gradually decreases with improvements in GPS technology.

3.3.2 Recommendations for data collection and study designs

To more accurately examine the determinants of cycling speed, it is recommended to better control for the confounders and missing variables through data collection strategies and study designs. Since targeted-segment-based and experiment-based studies typically examine specific determinants, it is essential for them to select segments where the concerned factors differ, and other potential confounders are as similar as possible. In particular, factors that heavily influence cycling speed, such as turns, intersections, and cyclist volumes, should be controlled for. For example, to examine the impact of bike lane types on cycling speed, Bernardi and Rupi (2015) chose three segments with different bike lane types, while their lengths, distances to the city centre and intersections, as well as the speed limitation of adjacent vehicle lanes, are almost the same. Besides site control, these studies can also collect relevant determinants in addition to their targeted factors and include them as covariates in the analysis. Whole-trip-based studies can simultaneously include relevant determinants to address this problem. This requires an understanding of potential determinants and their importance levels. Furthermore, some advanced analytical approaches, such as multilevel models, can also help control for confounding variables.

It is also recommended to improve the representativeness of participants. Targeted-segment-based studies observed naturalistic cycling at fixed sites (e.g., Boufous et al., 2018; Jin et al., 2017), and the representativeness of their observations depends on whether the selected sites and data collection time can represent the general situation of the study area. Therefore, the chosen sites and time should cover different cyclist groups and cycling purposes. Experiment-based studies (e.g., Kircher et al., 2018) and whole-trip-based studies (e.g., El-Geneidy et al., 2007; Yan et al., 2024) collect data by recruiting cyclists tend to have selection bias. People who are willing to participate in cycling-related research that requires tracking their trips tend to have a positive attitude towards cycling. Therefore, their cycling speeds may differ a bit from those of the overall cyclists. In addition, some studies have small sample sizes, further increasing the risk of bias and the influence of outliers. It is not easy to have a fully representative dataset; however, by collecting larger datasets, such as through smartphone apps (e.g., Flügel et al., 2017; Schuhmacher et al., 2025), it can achieve better representativeness and more accurate results.

3.4 Conclusion

We identified 34 papers that empirically examine the determinants of cycling speed, and most of them (n = 28) have been published since 2015. Three study designs can be recognised based on their data collection strategies. Eleven studies collect and use cycling data on targeted segments (targeted-segment-based studies); five experiment-based studies recruit cyclists to ride on designated routes. 18 studies collect and analyse cycling speed over entire trips (whole-trip-based studies). Most recent studies adopt a whole-trip-based design.

Although studies with all three study designs can contribute to understanding cycling speed, experiment-based and whole-trip-based studies are recommended over targeted-segment-based studies. The advantages of targeted-segment studies, namely easy data collection and in-depth understanding of the targeted factors, overlap with those of the other two types. Collecting many observations with less effort can be achieved in whole-trip-based studies by utilising smartphone apps, and an in-depth understanding of cycling speed is enabled through experiment-based studies. However, the disadvantages of targeted-segment-based studies, especially the loss of speed information and the unavailability of cyclist characteristics, cannot be easily solved. In contrast, the advantage of experiment-based studies, namely observing in-ride behaviour, can hardly be achieved by the other two study designs. Similarly, whole-trip-based studies are advantageous for capturing speed variability throughout a ride, analysing multiple influential factors simultaneously, and incorporating cyclist and bicycle characteristics. Moreover, improvements in GPS technology have further strengthened this study design by addressing limitations related to positional accuracy.

Regardless of the study design, a reliable result requires careful consideration of data collection issues related to confounders and cyclist representativeness, followed by the selection of analytical approaches appropriate for the data and research objectives.

Based on these findings, the following empirical chapters will employ a whole-trip-based design, collecting cycling data using GPS devices and investigating detailed speed variations within rides.

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Chapter 4: Cycling Speed Variation: A Multilevel Model of Characteristics of Cyclists, Trips and Route Tracking Points

This chapter is based on the following article:

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4.1 Introduction

Cycling is emerging in countries without a strong cycling tradition and expanding in countries where the bicycle already has a solid position (Harms & Kansen, 2018). Governments promote cycling for its societal and individual benefits, related to the environment, health, urban liveability and mitigating traffic congestion, while travel satisfaction is often higher than for other modes (De Vos, 2018). However, maximum cycling speeds are generally lower than for motorised transport, although short distances, particularly in urban areas, can sometimes be covered faster by bike than by car (Dill & Gliebe, 2008). This means that, in most cases, cycling takes more time than driving. In addition, distances covered are typically shorter; thus, in terms of travel times, the bicycle often loses out to other modes of motorised transport.

Travel time is so important because travel choices highly depend on it. In travel demand models, where travel is considered as a derived demand, travel time is assumed to involve a disutility that should be minimised (Mokhtarian et al., 2010). In evaluation studies, the value of faster travel is that it induces travel time savings (Small, 2012). In accessibility studies, travel time is an essential component as well (Geurs & van Wee, 2004). Applied to cycling, it can be assumed that a smooth flow and reduction of delays will make cycling more competitive with other modes of transport (Hamilton & Wichman, 2018). There are, moreover, other reasons why attention to cycling speed is important. First, higher speeds also increase accident risks (Haustein & Møller, 2016; Schepers et al., 2014; Schepers et al., 2017; Woodcock et al., 2014). Second, cycling speeds and the variety of speeds in everyday use tend to increase with the adoption of electric bicycles (Schleinitz et al., 2017). Furthermore, governments tend to build better infrastructure, such as bicycle express paths (Rayaprolu et al., 2020), enabling cyclists to increase their speeds.

Not only do maximum and average cycling speeds matter, but also variations during a trip. Cyclists prefer to cycle as smoothly as possible and to maintain their desired speed levels, taking into account safety. So, for planners, it is necessary to know to what extent speeds vary during trips. The average speed of cyclists says little about the obstacles they encounter on the route. Intra-trip speed measurement, however, provides insights into the locations where speed varies. By linking speed and characteristics of geographical positions, insights can be gained into the effect of infrastructure, urbanisation and traffic density on speed. Such insights help policymakers and road authorities to reduce or remove speed barriers.

However, remarkably little attention has been paid to the speed component of cycling in the literature (Strauss & Miranda-Moreno, 2017). The research that does, typically measures speed at fixed locations (e.g., Eriksson et al., 2019; Opiela et al., 1980), or considers the average speed of an entire ride (e.g., Schantz, 2017; Schleinitz et al., 2017; Stigell & Schantz, 2015) or at best speeds per trip segment (El-Geneidy et al., 2007; Flügel et al., 2019; Manum et al., 2017). Only a few studies have studied the factors that influence intra-trip speed variation (Arnesen et al., 2020; Clarry et al., 2019), and they only included a limited number of influencing factors. The background for a limited number of studies is highly likely that until recently, it was hardly possible to correctly register variation in cycling speed. GPS technology solved this problem (e.g., Bohte & Maat, 2009), as it allows researchers to obtain accurate information about variation in speed and related positions; through innovations in GPS technology, data quality has improved in recent years, so reliable speed measurements are now available.

The added value of this paper is that it aims to explain variations in cycling speeds on three levels. It departs from the promise that cycling speed varies (1) between cyclists, referred to as inter-person variation, (2) between trips of the same cyclist, referred to as intra-person variation, and (3) during the trip, referred to as intra-trip variation. The cyclist represents the first level, with factors that vary between persons, such as gender, age, health condition and preferences or attitudes, explaining inter-person variation. At the second level, a person makes multiple trips, with characteristics that may vary between trips but remain stable during the trip, such as the bicycle type or trip motive (e.g., commuting, leisure), which causes intra-person variation. The factors that are assumed to influence intra-trip variation, the third level, are infrastructural features and the land use, as well as local wind conditions and precipitation circumstances. By measuring the speed continuously for each geographical position during the ride, we identify the factors that influence speeds and, consequently, the intra-trip variation in speed. For this purpose, GPS devices continuously measure the so-called tracking points, i.e. the geo-positions and the corresponding clock times. We apply a multilevel approach, in which the independence of the observations, i.e. geopositions within trips and trips per respondent, is controlled for. This allows us to identify the contribution of each level and each factor. Data was collected in the Netherlands using a survey and recording by standalone GPS devices.

The paper is structured as follows. Section 4.2 discusses the empirical literature, both methods and results, followed by the methodology in Section 4.3 and modelling results in Section 4.4. Section 4.5 ends with conclusions, discussions and recommendations.

4.2 Literature Review

In this section, we examine how previous research collected cycling speed data, analysed speed variation, and what findings emerged from it.

4.2.1 Speed data collection

Speed data is collected in three ways: (i) at fixed locations, (ii) by measuring the start and end time of the ride, or (iii) by continuously tracking the cyclist using GPS-technology. Fixed location methods vary in degree of advancement, ranging from manual approaches, which require an observer during measurement (e.g., Thompson et al., 1997), to semi-automatic methods that register automatically when a cyclist passes (Hunter et al., 2009) or use frame-by-frame video camera analysis (Ling & Wu, 2004), while full automatic measurement and data extraction is the case for video cameras using computer vision (Kassim et al., 2017). These methods measure cycling speed at fixed locations over a period of time, so they only include the situation at certain locations and do not follow cyclists with their characteristics.

These shortcomings of measuring at fixed locations can be avoided by collecting data from trips, including characteristics of these trips and the corresponding cyclist. The most basic method is calculating the average cycling speed by using the departure and arrival times and the distance travelled. However, this is an inaccurate method. In many travel behaviour surveys, departure and arrival times are imprecisely measured, often relying on a posteriori estimation by the traveller (Kelly, 2013; Schantz, 2017). A slightly better method is to ask respondents to keep a diary, preferably filled in directly while travelling (Arentze et al., 2001). Another disadvantage is that the route and the exact distance are unknown (Sun et al., 2017). Solutions like asking routes in questionnaires (Munshi, 2016), calculating the shortest route assuming that this reflects the actual route to some extent (Dissanayake & Morikawa, 2002), or asking participants to draw their travel routes (Schantz, 2017) are not accurate.

The breakthrough in measuring speed came with the application of GPS-based devices. A GPS receiver determines its location by measuring the time that signals from at least four satellites reach it. GPS devices record position information, i.e. latitude, longitude, altitude and time stamps, every several seconds, so they are increasingly used to track the route and speed of travellers and their vehicles. In fact, the device produces a point trace of exact time-space stamps. For each point, the exact speed can be derived (Shen & Stopher, 2014), and infrastructure and environmental characteristics can be linked. Nevertheless, the satellite signal can be disturbed by environmental features, such as high buildings (Kassim et al., 2020), requiring preprocessing to remove noise. Also, detecting single trips from the raw GPS data involves intensive work and mistakes (Berjisian & Bigazzi, 2022). In addition, the sample size of studies with data from GPS devices is generally relatively small. There are now a handful of studies testing the determinants of cycling speed using data from GPS devices, although they all have less than 100 participants (El-Geneidy et al., 2007; Langford et al., 2015; Parkin & Rotheram, 2010; Schleinitz et al., 2018).

Standalone GPS devices require logistics, as the researcher has to distribute and collect them (Harding et al., 2020), making them difficult to deploy on a large scale; also, the respondent has to charge and carry devices with them daily. The use of smartphone tracking apps prevents these problems. They are technically similar to GPS devices; smartphones are widely available, and apps can be applied at lower costs as no extra device is needed (Romanillos et al., 2015). Studies using smartphone apps typically have larger samples; Strauss and Miranda-Moreno (2017) recruited 1000 cyclists, and Flügel et al. (2019) had 709 participants. B-Riders is a Dutch bicycle promotional program with over 8,500 participants (GoVelo, 2021; Romanillos et al., 2015), and the Fietstelweek (Dutch Bicycle Counting Week) collected more than half a million trips over several years. However, smartphone apps also have drawbacks, such as using excessive power and possible privacy concerns (Kanarachos et al., 2018; Tawalbeh et al., 2016), and they are as sensitive as standalone devices to recording errors (Harding et al., 2020).

4.2.2 Variation in speed

GPS-based studies can be further divided into the analysis of full trips, segments and tracking points. In the full trip approach, the average speed for the entire trip is calculated (e.g., Schleinitz et al., 2018), so it is only suitable for research into the characteristics of trips and cyclists. Segment approaches divide the trip into segments based on research purposes. The segment average speed is derived from the segment distance and travel duration (El-Geneidy et al., 2007; Flügel et al., 2019; Romanillos & Gutiérrez, 2020). Compared to the trip average speed, the segment speed gives additional insights into the speed variation during the trip. The division into segments is, however, often arbitrary.

The tracking point approach, however, is the most detailed in terms of 3D-geopositions and clock times, and is therefore the most accurate. Here, the speed at each tracking point is measured (Arnesen et al., 2020; Clarry et al., 2019). Since this approach is based on the travel time and distance between two tracking points, it is basically a segment approach with the shortest segments available, i.e. the segment between two consecutive tracking points. The closer the tracking points, the shorter the segments, and consequently the more detailed speed variations are recorded. In addition, environmental and infrastructure factors can be derived from spatial data sources at the tracking point level. More importantly, variables that change (almost) continuously during the ride, such as the slope, can be measured accurately. Therefore, studies using speeds at the tracking point level have the potential to reveal detailed influences of determinants on cycling speed variation. However, such studies should pay more attention to data noise than segment-based and trip-based approaches, as errors are not attenuated by average values of multiple tracking points (e.g., Arnesen et al., 2020).

4.2.3 Analysis methods

Early studies often used descriptive analysis to analyse cycling speed, comparing the cycling speed of different groups, such as men versus women, city bicycles versus electric bicycles and bike paths versus shared roads (e.g., Jensen et al., 2010; Lin et al., 2008). Others used OLS regression to estimate the impact of explanatory variables on speeds (Flügel et al., 2019). However, a fundamental assumption of OLS, namely independence of error terms, is unrealistic if a nested-data structure is assumed, which is the case with multiple trips per respondent, and multiple tracking points per trip (Romanillos & Gutiérrez, 2020). Only a few recent studies considered the independence of observations. Clarry et al. (2019) used cycling data from 4317 trips made by 518 cyclists to analyse the determinants of cycling speed at tracking points. They assumed that tracking points and segments are not independent but share common unobserved factors influencing cycling speed. To account for these unobserved factors, they estimated three multilevel models with random intercepts, i.e. a model with point and segment levels, a model with point, segment and cyclist levels, and a model with point, segment and trip levels. These models show the existence of common unobserved factors at each level (heterogeneity) and the importance of controlling for the non-dependence of observations. However, due to the absence of cyclist and bicycle characteristics, the heterogeneity of these levels has not been fully examined.

4.2.4 Factors determining cycling speed

Previous research has identified the effects of characteristics at different levels of aggregation, although a multilevel approach has been rare. At the level of the cyclist, it was found that men tend to cycle faster than women. This applies to both the average trip speed (Schantz, 2017) as well as the speed at every segment (El-Geneidy et al., 2007; Romanillos & Gutiérrez, 2020; Strauss & Miranda-Moreno, 2017). Age is negatively related to the trip average cycling speed (Schantz, 2017; Schleinitz et al., 2017) and the segment average speed (Romanillos & Gutiérrez, 2020). Cycling experience also plays a role, as shown by higher speeds among frequent cyclists (Poliziani et al., 2022) and those with winter cycling experience (Strauss & Miranda-Moreno, 2017). However, to the best of our knowledge, preferences like risk-taking, smooth cycling and health conditions have not been investigated yet.

The trip level characteristics may vary between rides of one person but remain constant during a ride. The bicycle type clearly influences the speed, with trips using speed pedelecs and conventional electric bicycles being significantly faster than those with city bicycles (Eriksson et al., 2019; Jin et al., 2017; Lin et al., 2008; Mohamed & Bigazzi, 2019; Schleinitz et al., 2018; Shen & Stopher, 2014). Commute trips have higher speeds than non-commute trips (Broach et al., 2012; Jensen et al., 2010). Current studies also regard weather conditions as constant during a trip, although weather can change during a ride. Romanillos and Gutiérrez (2020) found that speeds are higher on sunny days than on cloudy and rainy days, and Strauss and Miranda-Moreno (2017) found a positive effect of temperature on cycling speed. By contrast, a Dutch dataset indicated a higher cycling speed (17.8 km/h) in foggy or rainy weather compared to 17 km/h for all trips (Fietstelweek, 2017).

At the segment or point level, factor values depend on geo-positions. Land use usually varies during the ride and is considered as an independent characteristic or a bundle of characteristics. Cycling speeds in city centres are lower (Flügel et al., 2019; Gustafsson & Archer, 2013; Schantz, 2017), as higher densities of road users result in more interactions (Flügel et al., 2019; Gustafsson & Archer, 2013), and higher intersection densities cause more stops and delays (Plazier et al., 2017). Infrastructure also influences cycling speeds. Separated bicycle paths protect cyclists from other traffic, allowing cyclists to cycle faster (Clarry et al., 2019; El-Geneidy et al., 2007; Flügel et al., 2019; Kassim et al., 2019; Romanillos & Gutiérrez, 2020; Strauss & Miranda-Moreno, 2017), although two studies found the opposite (Bernardi & Rupi, 2015; Poliziani et al., 2022). Studies focusing on speeds at segments between intersections found that cycling speed at longer segments is higher than at shorter segments (Poliziani et al., 2022; Strauss & Miranda-Moreno, 2017), since cyclists can more easily cycle at their desired speeds. Wide bicycle lanes (Boufous et al., 2018; Garcia et al., 2015; Li et al., 2019), a smooth surface (Manum et al., 2017), and straight roads are positively related to cycling speed (Arnesen et al., 2020). Intersections or traffic lights involve deceleration or stops, so trip segments (Manum et al., 2017; Strauss & Miranda-Moreno, 2017) and points (Arnesen et al., 2020) close to intersections have lower speeds. Variations in slope show that cycling downhill is faster than uphill, an obvious result, while speed loss uphill is greater than speed gain downhill (Arnesen et al., 2020; Flügel et al., 2019; Parkin & Rotheram, 2010). Traffic intensity and the density of bicycles appear to be negatively related to speed (Li et al., 2019; Shan et al., 2015). This influence is greater for electric bicycles than city bicycles (Jin et al., 2017). Also, the presence of pedestrians reduces cycling speed (Bernardi & Rupi, 2015; Boufous et al., 2018).

4.2.5 Gaps and conceptual framework

Summarising sections 4.2.1 – 4.2.4, recent studies on cycling speed used data collected through GPS devices or smartphone apps. The unit of analysis for which the speed was calculated varied between the entire trip, segments within the trip, and tracking points. The latter two make it possible to analyse the intra-trip speed variation, but this has been rarely done and is considered a clear research gap. Furthermore, the influence of factors that determine speed should be distinguished on different levels: characteristics of the cyclist; characteristics of the trip, including the bicycle type; and route characteristics at different geopositions (tracking points), such as infrastructure characteristics, the environment and other traffic. The nested data structure is hardly considered in the literature, making it a second gap. Finally, except for age and gender, other cyclist characteristics, including cycling related preferences, were hardly examined.

This study departs from the gaps above. Cycling speed is assumed to be determined at three levels, as shown in the conceptual model (Figure 4.1). The model shows a multilevel structure and assumes that factors at each level explain a speed variation, i.e. between persons (inter-personal variation), between trips (intra-personal variation) and within trips (intra-trip variation). Both the multilevel structure and the intra-trip speed variation have hardly been applied to cycling, certainly not in combination. This study limits itself to three levels, though the bicycle used is in principle an independent level.

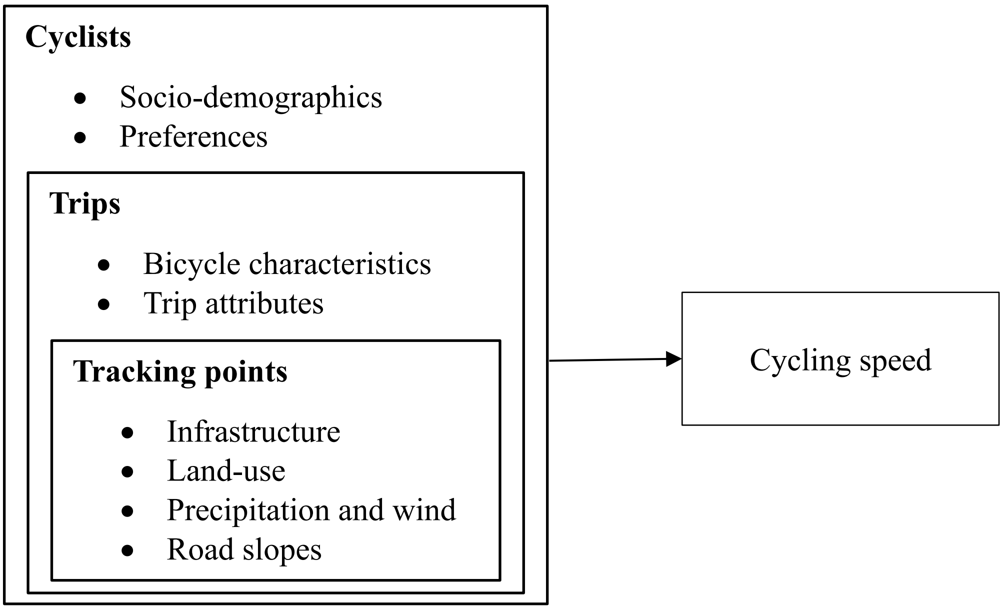

Figure 4.1: Conceptual model: the three-level multilevel model for cycling speed variation

4.3 Approach

4.3.1 Data collection

Data was collected in the Netherlands during the Covid-19 pandemic. Because random sampling or using panels was virtually impossible during the pandemic, we had to follow a less formal approach to recruit participants. Three graduate students recruited their relatives and friends for this purpose. Participants received an information letter outlining the study objectives, data pseudonymisation, and data safety. Along with the letter, they also received a standalone GPS device (Prime AT PLT) and a charging cable. They were asked to carry the GPS device, keep it in their bags or pockets, and charge it daily. The device was tested before collecting data and showed superior receiving sensitivity and high position accuracy. It records a timestamp every five seconds, including its geographical position (latitude, longitude and altitude) and speed. The respondents held this device for seven consecutive days between the end of November 2020 and the start of January 2021, and some of them also made a few trips (14%) during the Christmas and New Year holidays (23rd December to 3rd January). In addition, participants were invited to fill out a survey on their socio-demographics, bicycle ownership, cycling experience and preferences about cycling safety, smooth cycling and green areas. The changes in their cycling behaviour during the Covid-19 pandemic were also asked. 64 participants joined the study, resulting in 64 GPS data logs and 255,228 tracking points.

The sample shows an overrepresentation of students. Correspondingly, a large group of participants are young, healthy, have a high education level, a lower household income and limited access to cars. Females are also overrepresented. More than 80% of participants have commuting cycling experiences, and around half have cycled for leisure and exercise. They prefer safety, smooth cycling conditions and green areas. The Covid-19 pandemic caused a decrease in commuting cycling (work/study) and a slight increase in recreational cycling (leisure and exercise). The participants hardly intentionally avoided busy roads to reduce infection risks.

Participants cycled in 40 cities and towns, mainly in the city of Utrecht and its surrounding areas. The city of Utrecht, with a dense population of 3,709 inhabitants/km^2, is centrally located in the Netherlands. It has one of the best bicycle infrastructure systems in the Netherlands (Schering et al., 2022), resulting in a high bicycle modal share. In 2019, more than 46% of trips in Utrecht were made by bicycles (De Haas & Hamersma, 2020). Utrecht has a maritime climate with a mild and wet winter. The average temperature in December is 3.7°C, and the average cumulative precipitation is 76 mm. However, December 2020 was relatively warm (5.5°C) and rainy (107 mm), and no ice days occurred (KNMI, 2021).

4.3.2 Preprocessing

Raw data described all movements of the respondents during the data collection period. The preprocessing first detected bicycle trips from raw data, and then these trips were map-matched to the most likely routes.

The bicycle trip detection includes four steps, namely trip segmentation, potential bicycle trip detections, bus/tram trip removal and bicycle type confirmation. By employing trip segmentation, the raw data was split to derive separate single-mode trips (excluding walking). In a day, people may make many single-mode trips, between which they walk or participate in non-travel activities. So, a whole GPS log can be divided into single-mode trips after removing walking and non-travel activity points. We define walking points as continuous points with speeds between 1 km/h and 7 km/h with a total distance over 50 meters. Points that remain within a circular area with a 50-metre radius for more than three minutes were regarded as non-travel activity points. Second, we define city or conventional electric bicycle trips as trips with average speeds between 10 and 25 km/h and the 95th percentile speed below 30 km/h. Trips with average speeds ranging from 25 to 45 km/h and the 95th percentile speed below 45 km/h were assumed to be made by sport bicycles (racing bicycles and mountain bicycles) or speed pedelecs. Conventional electric bicycles can support pedalling up to 25 km/h, while speed pedelecs support up to 45 km/h. The 95th percentile speed was used to distinguish bicycle trips from bus/tram trips, as their average speeds can be similar in urban areas. Although conventional electric bicycles and speed pedelecs may occasionally exceed their designed maximum speeds, this happens infrequently. As observed by Herteleer et al. (2022), the average 95th percentile speed for speed pedelecs trips is 40 km/h. In contrast, buses and trams have frequent stops but can maintain relatively high speeds between stops. Third, considering that buses and trams may have a similar 95th percentile speed to bicycles in some urban areas and during congestion, we further detected possible bus/tram trips with their stop positions during trips and removed these trips from the result of the previous step. A stop was assumed to be made if the speed of a point is lower than 7 km/h, at which cyclists are unlikely to maintain balance. Multiple adjacent points with speeds below 7 km/h were recognised as one stop. After excluding stops at intersections, the remaining stops were compared with the positions of bus/tram stations. Trips with a high share of stops at bus/tram stations were recognised as bus/tram trips. However, none of the trips fell into this category. Fourth, the bicycle types for all potential bicycle trips were confirmed by additional survey data, including bicycle ownership data (most participants only own one type), the usage of bicycle types for different purposes, the home address and the work/study place address. Trip purposes (commuting to work or study/leisure/others) were derived from the locations of the trip origins and destinations. This information was combined to allocate the bicycle types to each trip. Occasionally, trips initially categorised as city bicycles/conventional electric bicycle trips were reassigned as sportive bicycles, as the participant only owns a mountain bicycle.

In total, 550 bicycle trips were detected, from which 42 trips shorter than 500 metres were removed, resulting in 58,979 tracking points from 508 trips made by 60 cyclists. No valid bicycle trips were recognised from the GPS data logs of four participants, and they were excluded from the analysis. Of these 508 trips, 454 are city bike trips, 24 are conventional electric bicycle trips, 30 are sportive bicycle trips and none of the trips are speed pedelec trips. Conventional electric bicycles account for 5% of all bicycle trips, lower than the Dutch average percentage of 18% (De Haas & Hamersma, 2020). This can be attributed to the overrepresentation of students and young cyclists in our sample, who are less likely to have electric bicycles (Boonstra et al., 2021).

Map matching is the process of finding the most likely route taken by cyclists based on tracking point locations (Romanillos & Gutiérrez, 2020). Its purpose is to link the infrastructure attributes from route maps to every tracking point. The method developed by Scheider (2017) was adopted to map match tracking points to the Fietsersbond network data (2018 version). First, all road segments within a threshold distance (25 meters in the present study) from tracking points were regarded as segment candidates. The match probability of a candidate decreases with its distance from tracking points. Second, the shortest path connecting segment candidates of two continuous points was found. If two continuous tracking points have 4 and 5 segment candidates respectively, there are at most 20 (4×5) possible paths. Similarly, shorter paths have higher match probabilities. Then, the overall match probability for a complete route was calculated by multiplying the match probabilities of its segment candidates and the paths connecting them. The route with the highest probability was chosen as the map-matched route, representing the most likely path taken by cyclists. The final step is the manual examination and correction of evident errors, which resulted in only a few corrections.

4.3.3 Variables

4.3.3.1 Speed and distance

Cycling speed at every tracking point is directly measured by the GPS device (the calculation method is not provided by its manual), and it can also be measured with locations and time stamps of two continuous points. In two previous studies which analysed cycling speed at tracking points, Arnesen et al. (2020) calculated speed with points' locations and time stamps, while Clarry et al. (2019) used speed from GPS devices. However, it is uncertain which method is more accurate for our study, so speed was measured with different methods and compared.

In our study, we compared three speed measurement methods: (i) the speed reported by the GPS device, (ii) by dividing the Euclidean distance between consecutive tracking points by their time interval, and (iii) by dividing the network distance and time interval. The network distance is the distance between two tracking points along the map-matched route in the digital road network. It is used because most raw tracking points are not precisely located on the digital road network due to GPS inaccuracies and map abstraction, so the line connecting the points may deviate a few meters and not perfectly reflect curved routes and turns. The three speeds are denoted as VD_i, VP_i and VN_i respectively, where VD refers to the speed measured by GPS devices, VP is the speed measured by Euclidean distance, VN is the speed measured by network distance and i is the point order in a trip. The measurement of VP_i and VN_i is:

$$VP_i = DP_{(i,i-1)} / T_{(i,i-1)} \tag{4.1}$$

where $DP_{(i,i-1)}$ is the Euclidean distance between points $i-1$ and i, and $T_{(i,i-1)}$ is the duration between these two points, and

$$VN_i = DN_{(i,i-1)} / T_{(i,i-1)} \tag{4.2}$$

where $DN_{(i,i-1)}$ is the network distance between points $i-1$ and i.

Table 4.1 and Figure 4.2 compare three ways of speed measuring. Table 4.1 shows that the maximum speed for VP_i is 80.43 km/h, and 117.75 km/h for VN_i, which are impossible in daily cycling. By contrast, VD_i ranges from 0 to 43 km/h, which is reasonable. Figure 4.2 compares one random ride as an example, showing a similar trend among the three speeds, especially at points with low or medium speeds. The main difference occurs at some points with a high speed, where VP_i and VN_i have evident outliers, consistent with the results in Table 4.1. In addition, VP_i, and especially VN_i have several points with speed increasing by more than 20 km/h from the previous point, which is hardly achieved in daily cycling. The substantial speed increase of VN_i is partially due to the map abstraction in certain turns, where curve turns are represented with two tangent lines. Therefore, tracking points at these turns have a larger network distance than the actual situation, resulting in a higher VN_i. In contrast, the highest speed and speed variation of VD_i are reasonable. All things considered, the speed measured by GPS devices (VD_i) was used in modelling.

Table 4.1: Speed calculation methods and speed summary

Name	Mean (km/h)	Min (km/h)	Max (km/h)	Std.dev.
Speed from devices (VD_i)	16.22	0	43.00	5.79
Speed measured by Euclidean distance (VP_i)	18.01	0.37	80.43	5.48
Speed measured by network distance (VN_i)	18.43	0.24	117.75	6.27

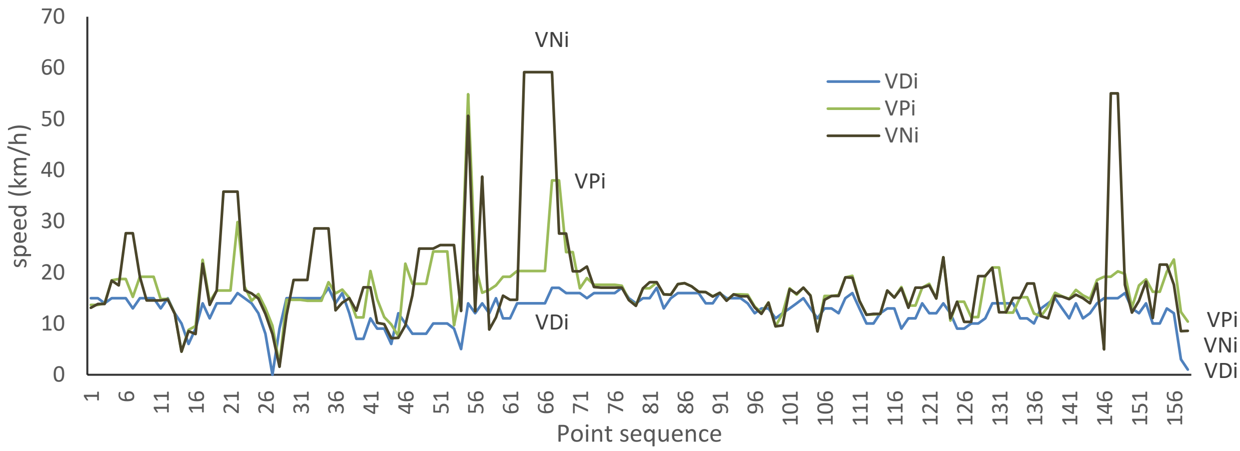

Figure 4.2: A sample of speed calculation methods comparison

The trip length is the network distance between the first and last tracking points, equal to the sum of the network distance between each consecutive pair of tracking points within the trip.

4.3.3.2 Turn and slope

Turns were derived from the direction change of the map-matched route segments, displayed in degrees of curvature, ranging from -180° to 180°. A turn is recognised if two consecutive segments formulate an angle greater than 80° (right turn) or lesser than -80° (left turn). Points within 30 meters of turns were then labelled as the part before or after right/left turns.

The road slope was calculated for each tracking point based on their altitudes and positions. Point altitudes were derived from a digital altitude map of the Netherlands (AHN, 2020) based on its coordinates. First, the tangent value of the slope gradient at tracking points i (T_i) was measured as:

$$T_i = H_{p(i,i-1)} / D_{p(i,i-1)} \tag{4.3}$$

where $H_{p(i,i-1)}$ is the altitude of points i minus the altitude of point $i-1$, and $D_{p(i,i-1)}$ is the network distance between these two points. Then, this value was converted to a degree. Considering that roads only with a gradient exceeding 3% (1.7°) can strongly influence cycling speed (Flügel et al., 2019), slopes were categorised into uphill (slope > 2°), flat road (-2° <= slope <= 2°), downhill (slope < -2°).

4.3.3.3 Infrastructure and land-use

Infrastructure attributes were taken from the Fietsersbond, which includes detailed road attributes. Different bicycle lane types are distinguished. Bike tracks refer to on-road bicycle lanes that do not have a physical transition between the road space for cyclists and motorised traffic; they may have different pavements or pavement colours. Bike paths along roads are physically separated bike lanes along main roads. Solitary bike paths are routes independent from main roads. Bike streets are a relatively new road type, designed as a street where bicycles have priority; motor vehicles are allowed but have to adapt to bicycles (Rivera Olsson & Elldér, 2023). Intersection types include signalised intersections, non-signalised intersections and roundabouts; the number of legs is not considered. The parts before and after signalised/non-signalised intersections are also recognised as a separate category.

Land-use types were calculated based on tracking point locations. The dominant land-use type within the circular buffer of a tracking point was considered as its land-use type. There are 13 land-use types in Bestand Bodemgebruik 2015, and they were categorised into five types: built-up (the area in use for residents, work, shopping, cultural facilities and public amenities), semi built-up (the area with a certain amount of paving, not in use as transport area or built-up area), transport (including airports, railways, the main road network, parking lots and bus stations), industry and nature area. Different buffer radii were used to calculate the dominant land-use type, with similar outcomes; finally, a 50-metre buffer was chosen.

4.3.3.4 Weather and night trip

Weather conditions, including temperature, precipitation, humidity, wind speed and wind direction, are recorded by the Royal Netherlands Meteorological Institute (KNMI) every 10 minutes for 33 weather stations in the study area. We took values from the nearest station. Temperature and humidity are regarded as trip-level variables since they hardly change during a short period. The temperature and humidity at the trip mid-time were regarded as the trip value. Wind and precipitation are likely to change constantly, and are point-level variables. Wind speed was classified as strong ($> 5.5\, m/s$), light ($1.5 - 5.5\, m/s$) and no wind ($<= 1.5\, m/s$), and directions as tailwind (direction difference < 67.5°), crosswind (67.5° <= direction difference <= 112.5°) and headwind (direction difference > 112.5°), combining into seven categories: no wind, strong headwind, strong side-wind, strong tailwind, light headwind, light side-wind and light tailwind. Precipitation was divided into heavy rain ($> 5\, mm/h$), light to medium rain ($0 - 5\, mm/h$) and no rain.

The night, the period without sunlight, was defined as the period between astronomical dusk and astronomical dawn. It changes daily. Trips that start at daytime but end at nighttime or vice versa, are allocated to the period with the longest duration.

4.3.4 Modelling method

Multilevel linear mixed-effects models are estimated in this study using the mixed command of Stata 17. It is a generalisation of linear regression in nested-data situations (Searle et al., 2009), allowing for the inclusion of fixed effects and random deviations (effects) other than those associated with the overall error term.

The present study uses a three-level nested data structure (cyclists, trips and points), and a three-level mixed-effect model can be expressed as:

$$y_{ptc} = \beta_0 + \sum_{g=1}^{d} \beta_g \mathrm{x}_{gc} + \sum_{j=1}^{b} \beta_j \mathrm{x}_{jtc} + \sum_{i=1}^{a} \beta_i \mathrm{x}_{iptc} + \mathrm{v}_c + \mathrm{u}_{tc} + e_{ptc} \tag{4.4}$$

where y_{ptc} is cycling speed at point p in trip t of cyclist c. The fixed part is $\beta_0 + \sum_{g=1}^{d} \beta_g \mathrm{x}_{gc} + \sum_{j=1}^{b} \beta_j \mathrm{x}_{jtc} + \sum_{i=1}^{a} \beta_i \mathrm{x}_{iptc}$, which specifies the overall mean influence of d cyclist-level, b trip-level and a point-level predictors on the cycling speed. Among these parameters, x_{gc} refers to the cyclist-level variables with slope β_g, x_{jtc} refers to the trip-level variables with slope β_j and x_{iptc} refers to the tracking point-level variables with slope β_i. The random part is expressed as $v_c + u_{tc} + e_{ptc}$ and assumed to be uncorrelated with independent variables. $v_c \sim N(0, \sigma_v^2)$ is the random effect of cyclist c, and the interpretation of σ_v^2 is the between-cyclist variance, adjusting for the predictors. This variance therefore measures the extent to which cyclist c varies from the fixed part. $u_{tc} \sim N(0, \sigma_u^2)$and $e_{ptc} \sim N(0, \sigma_e^2)$ have parallel interpretations.

Based on this, we first estimate a null model (Model 1) to check the speed variance components at different levels and the existence of cyclist and trip heterogeneity. Then cyclist-level and trip-level variables are added to Model 2 to explain inter-person and intra-person cycling speed variation, namely the cyclist and trip heterogeneity. Based on it, precipitation, wind, road slope and land-use are added to Model 3, and land-use is replaced by bicycle infrastructure in Model 4. These two models mainly explain intra-trip cycling speed variation. Land-use and bicycle infrastructure are modelled separately because of collinearity; for example, intersections are denser in built-up areas. Model 4 also introduces random slopes of some infrastructure variables across trips, i.e. before signalised, before left turns, before right turns, signalised intersections and pedestrian areas, since the influence of these variables is expected to vary across trips. For example, a racing bicycle may decelerate more than a city bicycle before a red light. The random slope model can help understand the differences in intra-trip speed variations between trips. Equation 5 is an example of the random slope model, allowing the coefficient of x_{1ptc} to be random at the trip level:

$$y_{ptc} = \beta_0 + \sum_{g=1}^{d} \beta_g x_{gc} + \sum_{j=1}^{b} \beta_j x_{jtc} + \sum_{i=1}^{a} \beta_i x_{iptc} + v_c + u_{0tc} + u_{1tc} \times x_{1ptc} + e_{ptc} \tag{4.5}$$

where $u_{1tc} \times x_{1ptc}$ is a new term compared to equation (4). Now the grand mean slope of x_{1ptc} is β_1, and the slope for the trip tc is $\beta_1 + u_{1tc}$. The covariance between the trip intercept ($\beta_0 + u_{0tc}$) and the trip slope ($\beta_1 + u_{1tc}$) is also calculated. It can describe how the influence of tracking point level variables changes across trips.

4.4 Result

4.4.1 Sample frequency

Participants show various trip frequencies and lengths (Table 4.2), therefore contributing differently to the dataset. This reflects the natural variation of cyclists in cycling behaviours. Table 4.2 classifies participants into four groups based on their trip frequencies. Most cyclists made fewer than ten bicycle trips, and a small number of participants made up to 24 trips. The average trip length of cyclists tends to decrease with their trip frequency. So, the difference in tracking point number between cyclists is smaller than the trip frequency. Those cyclists with frequent trips show a lower speed at tracking points.

Table 4.2: Sample frequency

Trip frequency	No. of cyclists	No. of trips per cyclist	Average trip length	No. of tracking points per cyclist	Average tracking point speed (km/h)
1 – 5	21	3.3	5.2	548	19.6
6 – 10	22	8.2	3.1	931	16.8
11 – 15	12	13.3	3.1	1653	14.5
16 – 24	5	19.8	1.7	1429	13.6
Total	60	8.5	3.1	983	16.2

4.4.2 Descriptive analysis

Table 4.3 describes all variables included in the final models, distinguishing the cyclist, trip and tracking point levels. It reports the mean tracking point speed from the GPS device for all dummy variables. Self-evaluated health conditions, preference for separate paths for safety and preference for high speed are continuous variables, using a scale ranging from 'strongly disagree' to 'strongly agree' (1 – 5). Around 60% of participants self-report a good health condition (Figure 4.3). Most cyclists prefer separate paths for safety, and even more cyclists try to maintain a high speed.

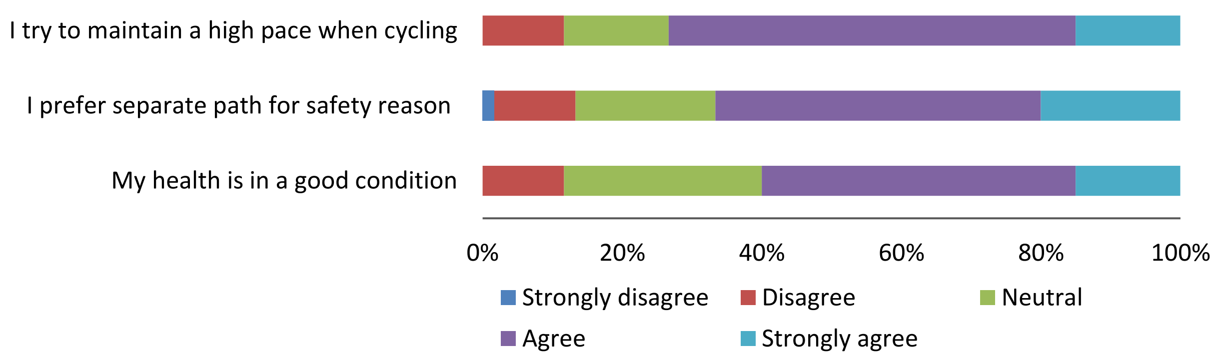

Figure 4.3: Opinions on statements about preferences and health conditions

Table 4.3: Variable descriptions

Variable	Description	Mean/%	Min./ Max.	Std.dev.	Mean point speed (km/h)
Cyclist level					
Cyclist					

Age		Continuous	35.4	16/74	16.7	
Male		Dummy (ref.)	33.3			18.6
Female		Dummy	66.7			14.6
Health condition		5-point Likert scale	3.6	2/5	0.9	
Preference separate path because of safety		5-point Likert scale	3.7	1/5	1.0	
Preference high speed		5-point Likert scale	3.8	2/5	0.9	
Trip level						
Bike type						
City bike		Dummy (ref.)	89.4			14.7
E-bike		Dummy	4.7			19.1
Sport bike		Dummy	5.9			23.2
Situations						
Non-Night trip		Dummy (ref.)	87.4			16.5
Night trip		Dummy	12.6			14.3
Trip length (km)		Continuous	3.1	0.5/80.1	4.9	
Humidity (%)		Continuous	91.1	63/100	7.1	
Temperature (°C)		Continuous	6.1	-2.4/12.6	3.2	
Tracking point level						
Weather conditions						
Rain intensity	No rain	Dummy (ref.)	82.0			16.3
	Light-medium rain	Dummy	17.8			16.0
	Heavy rain	Dummy	0.2			18.8
Wind	No wind	Dummy (ref.)	13.2			16.6
	Strong headwind	Dummy	6.5			14.2
	Strong side-wind	Dummy	4.5			15.3
	Strong tailwind	Dummy	5.6			16.3
	Light headwind	Dummy	18.6			15.7
	Light side-wind	Dummy	26.8			16.4
	Light tailwind	Dummy	24.8			17.1
Slope			0.0	-28.3/28		
Slope	Flat roads	Dummy (ref.)	96.9			16.3
	Uphill	Dummy	1.6			13.6
	Downhill	Dummy	1.5			14.6
Land-use						
	Built up area	Dummy (ref.)	52.1			14.8

Land-use	Semi built up area	Dummy	1.8			16.5
	Transport area	Dummy	7.5			16.9
	Industry area	Dummy	4.4			16.4
	Nature area	Dummy	34.2			18.2
Infrastructure						
Bicycle lane types	Pedestrian areas	Dummy	1.0			13.7
	Residential roads	Dummy (ref.)	40.6			16.2
	Bike street	Dummy	13.9			17.1
	Bike track	Dummy	0.9			16.8
	Bike path along road	Dummy	31.4			16.3
	Solitary bike path	Dummy	12.3			15.4
Bridge and tunnel	Non-bridge/tunnel	Dummy (ref.)	97.3			16.3
	Bridge	Dummy	1.7			13.9
	Tunnel	Dummy	1.0			14.4
Intersection	Non-intersection	Dummy (ref.)	96.1			16.3
	Roundabout	Dummy	1.1			15.6
	Non-signalised	Dummy	1.6			13.5
	Signalised	Dummy	1.2			12.1
Before/after intersection	Others	Dummy (ref.)	92.7			16.4
	Before signalised	Dummy	1.2			11.5
	Before non-signalised	Dummy	1.9			12.4
	After signalised	Dummy	1.6			15.6
	After non-signalised	Dummy	2.7			14.7
Before/after turns	Others	Dummy (ref.)	88.7			16.6
	Before right turn	Dummy	2.3			12.2
	Before left turn	Dummy	2.5			11.9
	After right turn	Dummy	3.0			13.9
	After left turn	Dummy	3.5			13.8

4.4.3 Model outcomes

4.4.3.1 Multilevel structure

We applied multilevel mixed-effects linear regression models for cycling speeds (Table 4.4). The final model is constructed step by step, with the columns showing the effect of adding levels, starting with the null model (1) followed by the cyclist and the trip level (2) and the tracking point level; the latter has been divided into land use (3) and infrastructure (4). The reported coefficients represent the estimated changes in cycling speed (km/h) for a one-unit change in independent variables when holding other variables constant. For example, the coefficient of the preference for separated paths in model 2 is -0.445, meaning that cycling speeds decrease by $0.445\ km/h$ with one level of growth in this preference. Similarly, for categorical variables, 0.891 for light-medium rain in model 3 means that cyclists tend to cycle 0.891 km/h faster in light to medium rain compared to no rain. Log-likelihood (LL) and Akaike information criterion (AIC) are two parameters to compare the model fits of different models, with higher LL and lower AIC meaning a better goodness of fit. Model 1 to model 4 show increasing model fits, where the effects of the variables are fairly stable, suggesting the robustness of these models.

The null model shows variance components (Random intercept in Table 4.4) of the cyclist (7.864), trip (5.474) and tracking point (13.132) levels. It shows that 29.7% $(7.864/(7.864 + 5.474 + 13.132)$ and 20.7% of the total variance in cycling speed are due to between-cyclist differences and between-trip differences respectively, while within-trip differences account for about half of the total variance (49.6%). Substantial variances at the cyclist and trip levels also illustrate the existence of cyclist heterogeneity and trip heterogeneity. With additional variables added, this variance is partially explained, and the remaining speed variance decreases as expected.

Table 4.4: Model Results

Variables	Model 1	Model 2	Model 3	Model 4
	Null model	Controlled for cyclist and trip level variables	Controlled for land-use	Controlled for infrastructure
Cyclist-level				
Age		0.012	0.009	0.006
Female		-1.054*	-0.835	-0.779
Health condition		0.422	0.415	0.375
Preference separated path because of safety		-0.445*	-0.450*	-0.452*
Preference high speed		1.259***	1.269***	1.274***
Trip-level				
Bicycles, city bike as ref.				
E-bikes		3.178***	3.001***	2.785***
sport bikes		4.158***	4.170***	4.304***

Trip length	0.115***	0.113***	0.095***
Night trip	-0.531	-0.555*	-0.485
Temperature	-0.017	-0.043	-0.032
Humidity	0.033*	0.024	0.021
Tracking point-level			
Slope, flat road as ref.			
Downhill		-0.666***	-0.593***
Uphill		-1.838***	-1.651***
Precipitation, no rain as ref.			
Light-medium rain		0.891***	0.888***
Heavy rain		3.167	3.418
Wind, no wind as ref.			
Light tailwind		0.615***	0.647***
Light side-wind		0.194*	0.101
Light headwind		-0.180	-0.173
Strong tailwind		1.642***	1.585***
Strong side-wind		0.465***	0.359**
Strong headwind		-0.024	-0.051
Land-use, built up area as ref.			
Semi built up area		0.150	
Transport use area		-0.482***	
Industry use area		0.301***	
Nature area		0.660***	
Bike lane, residential road as ref.			
Pedestrian areas			-0.769***
Bike street			0.775***
Bike track			0.824***
Bike path along road			0.361***
Solitary bike path			0.106*
Bridge/tunnel, non-bridge/tunnel as ref.			
Tunnel			-0.869***
Bridge			-0.855***
Intersection, non-intersection as ref.			
Roundabout			-0.711***
Non-signalised			-1.920***
Signalised			-3.597***
Before/after intersection, others as ref.			
After non-signalised			-0.567***

After signalised				-0.162
Before non-signalised				-2.274***
Before signalised				-3.894***
Before/after turn, others as ref.				
After right turn				-1.430***
After left turn				-1.160***
Before right turn				-2.394***
Before left turn				-2.448***
Constants	15.237	7.131***	7.472***	8.323***
Random intercept				
Cyclist variance	7.864	2.121	2.147	1.977
Trip variance	5.474	5.038	4.848	4.804
Tracking point variance	13.132	13.132	12.886	11.854
Random slope				
Cov.				-2.493
Slope variance of before signalised				12.367
Model fit				
LL	-160605.9	-160555.87	-159994.73	-157664.35
AIC	321219.8	321141.7	320047.5	315418.7

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

4.4.3.2 The influence of cyclist level and trip level variables

Cyclist characteristics influence the average personal speed, explaining the inter-person variation and the heterogeneity of cyclists. Two preferences significantly influence cycling speed. Cyclists who prefer high-speed cycle faster, while those who prefer separated bicycle paths because of safety concerns tend to cycle slower. Gender becomes insignificant after considering the land use and bicycle infrastructure.

Similarly, trip conditions influence the average trip speed and explain intra-person variation. Conventional electric bicycles are 3 km/h faster than city bicycles, and sport bicycles are 4 km/h faster. Longer trips tend to have a higher speed, but this effect is negligible. Dark conditions hardly influence cycling speed. Humidity and temperature have no influence.

4.4.3.3 The influence of tracking point level variables

Most tracking point level variables significantly influence intra-trip speed variation with intuitive effects. Slope, precipitation and wind are included in both Models 3 and 4. Results show that cycling uphill is 1.7 km/h slower than on flat roads. Unexpectedly, cycling downhill also decreases speed by 0.6 km/h. Cycling during light to medium rain is 0.9 km/h faster than in dry episodes, while heavy rain does not influence cycling speeds. Cycling with tailwinds and side-winds, especially the strong tailwind, is faster, while headwinds were found indifferent.

Land-use is added in Model 3, and bicycle infrastructure are added in Model 4. Compared to built-up areas, speeds are higher in natural and industrial areas, and lower in transport areas. Cycling on all types of bike lanes is faster than on residential roads; by contrast, cycling in pedestrian areas is slower. Bridges and tunnels are negatively related to speed. All three kinds of intersections decrease cycling speed, and signalised intersections have the greatest effect, reducing cycling speed by 3.6 km/h. Cycling before intersections and turns is over 2 km/h slower, while only about 1 km/h slower after the intersections/turns.

4.4.3.4 The random slope effect

The random slope for the variable "before signalised" is considered for each trip in Model 4. The covariance between the trip intercept and the trip slope of "before signalised" is -2.493, showing that the slope tends to be smaller with the increase in the trip intercept. In other words, high-speed trips decelerate more before signalised intersections. This effect also applies to signalised intersections, pedestrian areas and before/after intersections/turns, meaning their negative effects on cycling speed are stronger for trips with higher speeds. Also, the effect of after-turns and intersections is less than before.

4.5 Conclusion

4.5.1 Conclusions and discussion

This paper aims to explain variations in cycling speeds on three levels, i.e. (1) between cyclists, referred to as inter-person variation, (2) between trips of the same cyclist, referred to as intra-person variation, and (3) during the trip, referred to as intra-trip variation. The null model shows the existence of heterogeneity between the levels. About 30% of the speed variance is attributed to the heterogeneity between cyclists, 21% to the trips, and 49% to differences within trips.

The cyclist-level variables explain the variation in speed between cyclists and the heterogeneity between them. As in other studies (Boufous et al., 2018; El-Geneidy et al., 2007), women cycle more slowly than men. Remarkably, however, this difference disappears after controlling for wind, precipitation, land use and bicycle infrastructure, suggesting that women may have different route choices, and respond differently to weather, thus avoiding speed reduction. Additionally, unlike most existing studies (Schleinitz et al., 2017; Vlakveld et al., 2015), age does not influence cycling speed. A possible reason is that older people tend to use electric bicycles more often, which compensates for the decline in physical abilities. It is worth noting that the absence of an age and gender effect is also possibly due to the relatively small and less representative dataset. A novel finding is that personal preferences clearly play a role, as expressed by the correlation between the preference for separate, thus safer tracks and lower speeds, and the finding that the preference for high speed correlates with an actual higher speed.

The trip-level variables show that electric bicycles appear to be faster than city bicycles, which was also found by previous studies (Eriksson et al., 2019; Jin et al., 2017; Schleinitz et al., 2017); sport bicycles are even faster, as these bicycles are designed for a high speed and often used for exercise. Contrary to previous studies suggesting an influence of temperature (Strauss & Miranda-Moreno, 2017) and humidity (Liu et al., 2017) on cycling speeds and bicycle trip generation, our findings indicate that humidity and temperature did not affect cycling speed. A possible reason is that temperature and humidity varied less during the data collection period.

The tracking point level variables, measuring differences during trips, are hardly investigated in the literature, so they provide interesting, partly unexpected findings. First, the role of slopes: it appears that not only cycling uphill (Arnesen et al., 2020; Flügel et al., 2019) reduces speed, but also downhill. This is because most slopes in the Netherlands are short, such as bridges, which often end on another road or at a junction, causing cyclists to go down carefully.

Secondly, wind effects on speeds are partly as expected: tailwinds increase cycling speed, but surprisingly, headwinds have no effect. Light to medium rain is associated with a $0.9\ km/h$ higher speed, suggesting that cyclists speed up to minimise exposure to rain, but self-selection may also play a role, namely people who choose cycling during rainy days may have better cycling abilities and so a higher speed. Heavy rain, however, does not affect cycling speed; a possible explanation could be that safety considerations discourage cyclists from cycling faster for a short exposure duration.

Third, with respect to land-use, being the landscape a cyclist crosses, we found that natural areas facilitate slightly faster cycling compared to built-up areas, as cyclists can cycle more unhindered, and decelerate and accelerate less frequently due to fewer crossings. People also ride faster in industrial areas, possibly because they are more often commuters. By contrast, cycling speeds in areas mainly used for transport are lower than in built up areas, probably due to complicated traffic conditions, including parking and bus docking.

Fourth, infrastructure characteristics play a key role in cycling speeds, and effects are largely as expected. Intersections and turns are the main barriers to cycling smoothly. Similar to other studies (Clarry et al., 2019; Strauss & Miranda-Moreno, 2017), cycling speeds at intersections, especially at signalised intersections, are relatively low. Interestingly, we also find that cycling within 30 metres before intersections is even slower than cycling at intersections. This is because cyclists slow down and even stop before entering an intersection, whereas they usually do not stop when passing intersections. The same effects are observed for turns. In addition, it is found that cyclists with higher speeds encounter a greater need to slow down when close to intersections and turns. This makes sense, but it also clearly shows that barriers to fast riders, for example electric bicycles, are even more of a hindrance.

Surprisingly, however, the influence of bike lane types is slightly different from existing studies (El-Geneidy et al., 2007; Flügel et al., 2019), who found that separated bike paths increase cycling speed. The highest speeds are found on bike tracks without physical separation from motorised vehicles. A possible reason is that cyclists receive pressure from other traffic (Poliziani et al., 2022), so they cycle faster to leave bike tracks quickly. Another explanation is that cyclists using bike tracks not separated from motorised vehicles are the more experienced cyclists. A third explanation is that cyclists can more easily swerve around other cyclists here. Bike streets also have higher speeds, though motorised vehicles are not excluded. They are usually located in residential areas with relatively lower traffic volume, while cyclists have priority on this road type, so they can cycle smoothly with less disturbance. Solitary bike paths are often used for leisure trips, which are partly faster if used by people with racing bikes, but also partly slower because several people cycle relaxed on such trips. In addition, cyclists with safety concerns also cycle here at a lower speed. Paths along main roads are busy, resulting in frequent interactions between cyclists. To summarise, the positive effects of separate paths are smaller than those of bike tracks and bike streets.

4.5.2 Implications and recommendations

Cycling speed is related to other cycling behaviours, such as safety, mode choice and cycling route choice. Insights into intra-trip speed variation are of great importance for modelling bicycle traffic. In addition, results about cycling speed variation support urban and infrastructural planning for better bicycle infrastructure (Parkin & Rotheram, 2010).

Incorporating speed variations between cyclists, trips, conditions and spatial-infrastructural situations in traffic models is believed to improve the model accuracy (Romanillos & Gutiérrez, 2020). For example, the inclusion of heterogeneous speeds of cyclists in bicycle congestion models successfully predicted longer delays for cyclists with high desired speeds (Paulsen et al., 2019). Paulsen and Nagel (2019) also indicated that bicycle congestion models can be further improved by considering delays at turns and intersections. However, due to an insufficient understanding of cycling speed variation along routes, traffic models often assume a constant speed (e.g., mode choice models, as shown by Ton et al., 2019) or struggle to accurately account for speed differences among infrastructure. For instance, Castro et al. (2022) modelled cycling speeds on a bicycle path with a 3% gradient with the traffic flow simulator VISSIM, but did not predict correct speed distributions, possibly because of the omission of other infrastructure characteristics influencing speeds. By including the speed differences in models, more accurate predictions can be made regarding mode choice and cycling accessibility, as the total trip time can be predicted more correctly (El-Geneidy et al., 2007). Moreover, destination and route choice can be better predicted because both depend on cycling speeds (Flügel et al., 2019).

For urban and infrastructural planners, understanding the variation of cycling speed can be used to design better cycling networks, which enable fast and smooth cycling and thus make cycling more competitive with other modes of transport. This knowledge can provide insights into ‘black spots’ where bicycle speed seriously drops. These fine-grained spatial insights enable a targeted, tailor-made approach. For example, some intelligent traffic light systems can be installed at intersections where cyclists experience long waiting times; providing more space for cyclists at intensively used segments, such as bike lanes along main roads, can prevent cyclists from reducing their speeds sharply. Moreover, it is possible to develop fast routes, which can be advised to cyclists, especially those prefer a constant and higher speed, i.e. cyclists with sporty and electric bicycles. Such routes can, for example, result from linking multiple bicycle streets.

4.5.3 Future research

By studying bicycle speed in a multilevel setting, using a broad dataset, this study has provided an impetus to explore bicycle speed in depth. To this end, a number of indicators and models have been developed that can be further refined in future research.

First, the present study addressed many bicycle speed influencing factors, including socio-demographics, bicycle types, bicycle infrastructure characteristics, weather conditions, etc.

However, the data collected during the COVID-19 pandemic caused a small and less representative sample and limited variation in bicycle types. Although we consider this dataset to be fit for such an analysis, the small dataset may limit the generalizability of the findings to the broader population, particularly for cyclist and trip level variables. So we recommend a larger and more representative sample, to consider a richer set of variables, including different age groups, trip purposes, time of day and bicycle types, as well as their interaction effects. We also recommend to identify and control for possible confounding variables, such as the bicycle type choice across age groups, and cycling frequency and distance between genders.

Second, because cyclists might choose a residential area and cycling routes that match their cycling speed preferences, self-selection effects can easily occur, influencing the results. Moreover, the degree to which people like cycling leads to self-selection by the degree of use, type of bicycle, and destination. An avenue for future research is to explore the occurrence and impact of such self-selection effects. Such effects are usually analysed by including attitudinal data in a longitudinal model, e.g., using structural equation models (e.g., Hamaker et al., 2015; Van De Coevering et al., 2021).

Third, it can be assumed that cyclists not only prefer a higher cycling speed but also a stable cycling speed. After all, both braking and accelerating require extra physical and mental effort and possibly increase risks. That is why additional research could focus on the extent of speed stability and where or in which situations cyclists can maintain stable speeds.

Fourth, cycling is more sensitive to weather conditions than other transportation modes, and this study reveals that weather also affects cycling speed. However, the differences in weather conditions during our observations were limited. It may even be assumed that potential cyclists will refrain from cycling when it rains, if barriers make travel times longer than strictly necessary. It therefore makes sense that some traffic lights nowadays give cyclists priority when it rains. With climate change, weather conditions tend to be more extreme and unpredictable, and the influence of weather on cycling speed is expected to increase. Consequently we advise more research into the impact of weather on cycling speeds, preferably based on year-round weather conditions.

To conclude, knowledge about cycling speed used to be almost non-existent, but with the increasing use of bicycles, the increasing stimulation of bicycle use and the greater variation in bicycle types, in particular the variety of electric bicycles, these insights are highly necessary and valuable. Based on the results of the current study, we can conclude that better cycling routes stimulate faster and smoother cycling. Any form of cycling facilities, such as cycle paths, cycle lanes and cycle tracks, can support high speeds. This also applies to the removal of speed-limiting factors. Therefore, more routes without barriers and with facilities specifically for bicycles are essential for cycling to be smooth and fast.

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Chapter 5: Cycling Speed and Weather: Roles of Cyclist Weather-Sensitivity, Spatial and Infrastructural Conditions

This chapter is submitted to a journal:

Yan, H., Maat, K., & van Wee, B. Cycling Speed and Weather: Roles of Cyclist Weather-sensitivity, Spatial and Infrastructural Conditions.

5.1 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 car use (Jonkeren, 2020). Therefore, an increasing number of studies examine the influence of weather on cycling behaviour. So far, most studies focus on mode choice, namely the choice between cycling and other transport 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 behaviour.

We hypothesise that weather affects cyclists' physical and mental feelings and experience in three aspects, all related to cycling speed, and ultimately affects travel time (Figure 5.1).

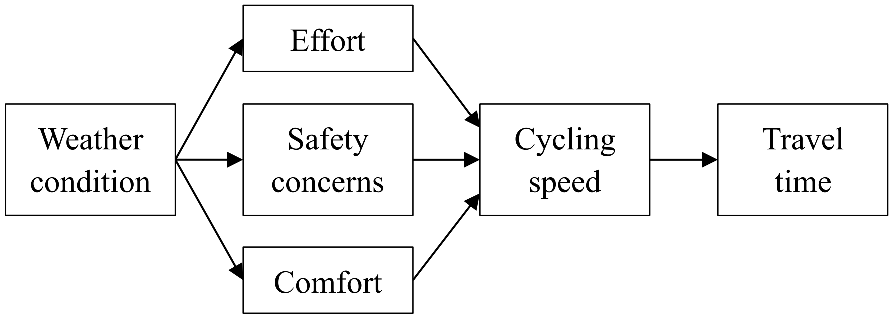

Figure 5.1: Conceptual model of the influence of weather on cycling speed

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., 2024). 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. Also, sometimes people ride faster to shorten their exposure to weather conditions such as rain, causing discomfort (Fietstelweek, 2017; Yan et al., 2024). 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 rain, snow and ice, cyclists become cautious and will often slow down (Shoman et al., 2023). Conversely, cycling during thunderstorms can be expected to be faster because of the risk of lightning strikes.

Ultimately, the changes in cycling speed due to weather conditions affect the travel time of cycling trips (assuming constant origins 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 motorised modes.

However, we do not assume that this applies to all cyclists to the same extent. Cyclists have different feelings towards 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 to be 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 also 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).

Individual impacts of weather on cycling speed lead to broader societal impacts. Longer travel time, extra effort, less comfort and higher risks experienced, due to the effect of bad weather on cycling speeds, decrease the share of cycling during bad weather and can lead to changes in the destinations of cyclists. In addition, bad weather may determine the overall perception of cycling; for example, the risk of precipitation or strong winds is too great to cycle anyway.

In addition, 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 hypothesise 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 analysed. 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 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 5.2 briefly reviews the literature and outlines research aims and assumptions. Section 5.3 describes the data and methods, and Section 5.4 illustrates key results, followed by conclusions and discussions in Section 5.5.

5.2 Literature Review

5.2.1 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 in weather-sensitivity groups. This is followed by discussing the still-limited evidence about the direct influence of weather on cycling speed. Then, the influence of other factors on cycling speed is briefly summarised.

5.2.2 Weather's effects on cycling behaviour 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., 2021; 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℃ (Böcker et al., 2019; Böcker & Thorsson, 2014; Helbich et al., 2014).

5.2.3 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 during 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 show the existence of different weather-sensitivity groups.

5.2.4 The influence of weather on cycling speed

Only a few studies have tested the influence of the weather on cycling speed, mainly focusing on precipitation. Snow and snowy surfaces decrease cycling speed significantly by around 15% due to cyclists' cautiousness to avoid possible risks, such as slipping (Shoman et al., 2023). Rain also affects cycling speed; Romanillos and Gutiérrez (2019) 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. (2024), 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. (2024) 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 $10-20°\mathrm{C}$ 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.

5.2.5 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. (2024) 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 infrastructure, 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 centres, urban areas and built-up areas, a lower speed is observed than in rural areas.

5.2.6 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 to occur: weather-sensitive cyclists are less inclined to cycle in bad weather, so trips made during bad weather are mainly from less-sensitive cyclists. Without considering this weather-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.

5.3 Data and Method

5.3.1 Overview of method

A GPS-tracked dataset of cycling trips is used, where a cyclist makes multiple trips, and a trip consists of a series of tracking points (Section 5.3.2.1). A factor mixture model was estimated to distinguish weather-sensitive groups (Section 5.3.3). Then, due to a hierarchical data structure (cyclist, trip and tracking point levels), multilevel models (Section 5.3.4) are estimated to account for the dependence of observations.

Figure 5.2 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, therefore, 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 5.3.2.4) to represent geographic differences. Wind shelter actually influences wind conditions, then cycling speed, but data for the required detailed wind conditions are unavailable, so we included the interaction term between shelter and wind (arrow I.2), which has a similar function, 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.

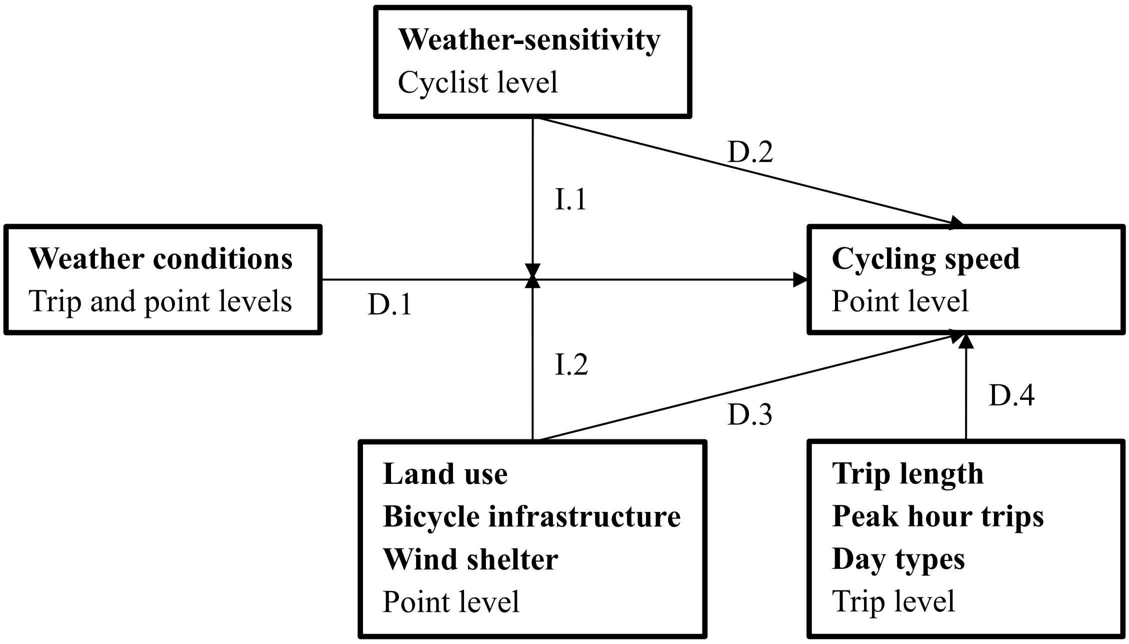

Figure 5.2: The model specification for the influence of weather on cycling speed

5.3.2 Data, study area and variables

5.3.2.1 Cycling data and study area

Cycling data is derived from the Sniffer Bike project (Snuffelfiets, 2020), which aims to support research to expand the 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 seconds, making it possible to get detailed cycling speed variation 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 in the present study is a subset taken from January 2021 to October 2023; data before 2021 was left out to reduce COVID-19's influence. During this period, 267 cyclists registered 96,413 potential bicycle trips. 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 minutes) 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 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 5.3.3), as it is not likely to detect accurate weather-sensitivity of cyclists with few trips. Further, some trips outside the study area or lacking infrastructure information were excluded from modelling, which removed three cyclists. The final dataset comprises 224 cyclists who made 65,196 rides, resulting in 5,260,355 tracking points.

The study area is centrally located in the Netherlands and includes the province of Utrecht and its adjacent municipalities (Figure 5.3). 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 weather station, the most central station of the Royal Netherlands Meteorological Institute (KNMI) in the study area, measured 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.

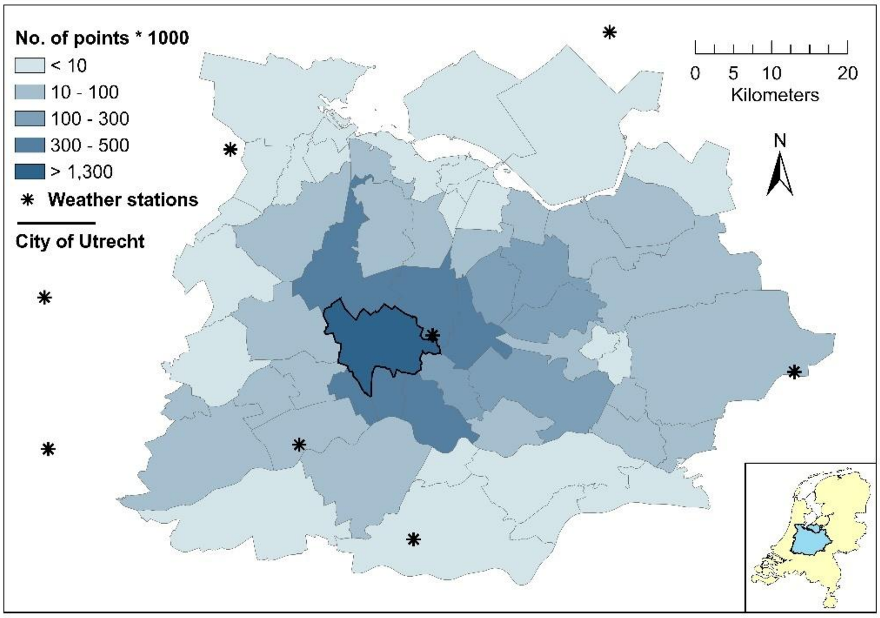

Figure 5.3: Study area, weather stations and tracking points distribution across municipalities

5.3.2.2 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.

5.3.2.3 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 measured by eight automatic weather stations in the study area

(Figure 5.3). The weather dataset consists of four basic weather components (temperature, humidity, precipitation intensity and wind speed), which are recorded every 10 minutes, 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.

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 the 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 within a bicycle trip duration 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; it is common in the Netherlands that people check precise rain forecasts before making a trip, especially in a situation of high rain possibility. 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 ($> 5.5 \text{ m/s}$), light ($1.5 - 5.5 \text{ m/s}$) and no wind ($< 1.5 \text{ m/s}$), 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 ℃), moderate/warm ($10 - 25$ ℃) and hot (> 25 ℃). 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 below the horizon more than 18° (between astronomical dusk and astronomical dawn) and twilight with the sun being 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 labelled as 'yes' if there is rain within half an hour after the trip. However, the near future rain condition is

[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.

highly correlated to the precipitation during the trip, showing collinearity, so it was not included in the final analysis.

5.3.2.4 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 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 an inconsistent L_R/H ratio, ranging 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).

5.3.2.5 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-metre 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, separate from motorised traffic with road markings or different pavements, bike streets where motorised vehicles are allowed but bicycles have priority (Rivera Olsson & Ellder, 2023), bike paths along roads, physically separate from motorised traffic, and solitary bike paths independent from main roads. Intersections were classified into intersections with traffic lights, intersections without traffic lights and roundabouts. Based on this, the road within 30 metres 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 recognised if a tracking point is within 30 metres of a turn, and the turn exceeds 80°. Bridges and tunnels were categorised as bridges, tunnels and regular roads.

Slope was calculated with the altitude from a 0.5 metre resolution altitude map of the Netherlands (AHN, 2020). First, all tracking points obtained 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 categorised into uphill (slope > 2°), flat road (− 2° < = slope < = 2°), and downhill (slope < − 2°).

5.3.2.6 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.

5.3.3 Cyclist weather-sensitivity detection

Following the literature, it was assumed that the underlying structure of people's weather-sensitivity is simultaneously categorical and continuous. First, distinct groups exist regarding the acceptance of weather (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. So, 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). It 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 models (FMM) were estimated to recognise 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, 2014). 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 behaviour 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 the ordered sensitivity dimension within a class means the existence of local dependence; for example, rain often accompanies a decline in temperature.

For this purpose, five class indicators were calculated with raw weather data for each cyclist, including the average monthly standard deviation of temperature (℃), 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 the sensitivity to rain, and a higher ratio means low sensitivity to rainfall. This ratio aims 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 deviations 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:

$$SD_{wci} = \sqrt{\frac{\sum_{r=1}^{R_{ci}}(x_{wcir}-\mu_{wci})^2}{R_{ci}}} \tag{5.1}$$

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 from 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:

$$SD_{wci} = \sqrt{\frac{\sum_{p=1}^{P_{ci}}(x_{wcip} - \mu_{wci})^2}{P_{ci}}} \tag{5.2}$$

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:

$$SD_{wc} = \frac{\sum_{i=1}^{n} SD_{wci}}{n} \tag{5.3}$$

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:

$$L_c = \frac{\sum_{r=1}^{R_c} \sum_{p \in rain(r)} D_{rp}}{\sum_{r=1}^{R_c} \sum_{p=2}^{P_r} D_{rp}} \tag{5.4}$$

where L_c is the rain length ratio for cyclist c, R_c is the total trip number made by cyclist c, P_t 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 t 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.

5.3.4 Multilevel modelling

Multilevel models with random intercepts were estimated to explore weather's influence on cycling speed, using the mixed command in Stata 18. It fits the hierarchical data structure of the current cycling dataset: tracking points are nested within trips, and trips are nested within cyclists. The model includes a random intercept for each cyclist, allowing 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 on the trip level reflect inherent differences between various trips of a cyclist. In other words, random intercepts capture the dependence of observations within the same group, ensuring reliable results.

5.4 Result

5.4.1 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 5.1).

Table 5.1: 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

5.4.2 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 converge during parameter estimation, when they have two or three latent classes and one factor. Therefore, the optimal class number is 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.

Table 5.2: Fit indices for four converged FMM models

Model		LL*	AIC	BIC	ABIC	Entropy	BLRT	LMR
FMM with only variant factor mean	2-class	-361.6	747.3	788.4	750.3	0.803	<0.001	0.036
	3-class	-324.5	677.1	725.0	680.6	0.828	<0.001	0.240
FMM with all variant parameters	2-class	-136.0	336.0	445.6	344.2	0.933	<0.001	0.329
	3-class	-32.5	161.0	325.4	173.4	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

All fit indices, except for LMR, show that the least restrictive FMM with the three-class, one-factor is the best solution (Table 5.2). 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 class less (Lo, 2001), and a significant p-value confirms the better estimation 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 variant 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, 2014; Muthen, 2003). From here, only the two least restrictive FMMs were 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 5.3). The three-class solution also recognised 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.

Table 5.3: 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%

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 the other two groups.

Less-sensitive cyclists generally make more trips and have a higher percentage of winter trips (Table 5.3). 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.

5.4.3 Descriptive analysis of multilevel model variables

Table 5.4 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 all dummy variables. The variables 'Sunshine duration' and 'Wind shelter' range between 0 and 1. Minimum and maximum trip lengths are 0.5 km 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.

Table 5.4: Descriptive statistics

Variable	**Obs.**	**Share**	**Mean (Std. Dev.)**	**Avg speed (km/h)**
Cyclist level variables	**224**			
Weather-sensitivity group				
Weather-sensitive group	46	20.5%		19.9
Less-weather-sensitive group	157	70.1%		19.1
Less rain-sensitive group	21	9.4%		17.6
Trip level variables	**65,196**			
Temperature				
<10	23,595	36.2%		18.2
10-25	39,235	60.2%		18.3
>25	2,366	3.6%		18.5
Humidity				
<70	29,901	45.9%		18.3
70-90	25,284	42.0%		18.2
>90	10,011	38.6%		18.3
Fog				
Yes	942	1.4%		18.3
No	64,254	98.6%		18.3
Snow				
Yes	293	0.4%		17.4
No	64,903	99.6%		18.3
Thunder				

Yes	773	1.2%		18.3
No	64,423	98.8%		18.3
Ice occurrence				
Yes	103	0.2%		17.1
No	65,093	99.8%		18.3
Sunshine duration			0.4 (0.42)	
Light conditions				
Daylight	56,997	87.4%		18.3
Twilight	5,912	9.1%		18.6
Darkness	2,287	3.5%		18.0
*Trip length (*km*)*			5.4 (6.4)	
Peak hours				
Off-peak	56,997	65.8%		18.3
Morning peak	5,912	12.7%		18.6
Evening peak	2,287	21.5%		18.0
Day type				
Weekday	50,264	77.1%		18.4
Weekend	13,507	20.7%		17.7
Holiday	1,425	2.2%		18.0
Point level variables	**5,260,355**			
Precipitation				
No rain	4,902,365	93.2%		19.1
Rain	357,990	6.8%		18.8
Wind				
No wind	526,625	10.0%		19.5
Light tailwind	1,470,609	30.0%		19.7
Light crosswind	988,156	18.8%		19.1
Light headwind	1,518,413	28.9%		18.5
Strong tailwind	269,952	5.1%		19.7
Strong crosswind	192,103	3.7%		18.7
Strong headwind	294,497	5.5%		17.5
Wind shelter			0.07 (0.20)	
Land use				
Built-up	1,933,320	36.8%		17.9
Semi-built-up	102,125	1.9%		18.5
Transport use	406,009	7.7%		18.5
Industry use	367,560	7.0%		19.3
Nature area	2,451,341	46.6%		20.1

Bike lane type				
Pedestrian area	24,187	0.5%		16.2
Residential road	2,016,727	38.3%		19.0
Bike street	564,333	10.7%		19.8
Bike tracks	156,156	3.0%		19.3
Bike path along main road	1,677,758	31.9%		19.2
Solitary bike path	821,194	15.6%		18.5
Intersection type				
Non-intersection	5,101,165	97.0%		19.2
Roundabout	30,155	0.6%		16.4
Intersection without traffic lights	56,820	1.1%		16.0
Intersection with traffic lights	72,215	1.4%		11.4
Intersection adjacent				
Others	5,061,074	96.2%		19.1
Before no light	49,689	0.9%		18.6
Before light	51,621	1.0%		17.3
After no light	47,938	0.9%		17.0
After light	50,033	1.0%		15.8
Turn				
Non-turn	4,476,615	85.1%		19.6
Before right	270,718	5.1%		17.0
Before left	293,983	5.6%		16.8
After right	109,977	2.1%		14.7
After left	109,062	2.1%		14.6
Bridge/tunnel				
Tunnel	61,748	1.2%		19.1
Normal	5,105,108	97.0%		19.1
Bridge	93,499	1.8%		16.9
Slope				
Flat	5,144,498	97.8%		19.1
Downhill	52,233	1.0%		17.9
Uphill	63,624	1.2%		16.2

5.4.4 Multilevel model results

5.4.4.1 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 5.5) show that 27.4% (7.250/(7.250+5.2+14.047)) of speed variance is between cyclists, and 19.6% is between trips. It illustrates the inherent speed differences between cyclists and between trips of a cyclist, showing the necessity of estimating multilevel models. From the Null mode to the Full model, the remaining unexplained variance keeps decreasing, and the model fit is gradually improved, illustrating that the added variables explain speed variation. 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 (-0.863) in the second model means that cycling speed is 0.863 km/h lower during snow than in a clear situation.

Table 5.5: 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		0.389	0.389	0.441
Less-rain-sensitive group		-0.351	-0.391	-0.200
Trip level variables				
Temperature, 10-25 °C as ref.				
<10		-0.145***	-0.147***	-0.143***
>25		0.022	0.021	0.023

Humidity, 70-90% as ref.				
<70		-0.097***	-0.098***	-0.058***
>90		0.087***	0.087***	0.006
Fog		0.217***	0.216***	0.199**
Thunder		0.008	0.009	0.100
Sunshine duration		0.003	0.003	-0.006**
Snow		-0.863***	-0.863***	-0.917***
Ice occurrence		-0.711***	-0.714***	-0.510**
Light conditions, daylight as ref.				
Twilight		-0.097***	-0.097***	-0.257***
Dark		-0.231***	-0.231***	-0.134***
Trip length				0.070***
Peak hours, off peak hour as ref.				
Morning peak hours				0.545***
Evening peak hours				0.169***
Day types, weekdays as ref.				
Weekend				-0.462***
Holiday				-0.642***
Point level variables				
Rain		0.001	-0.124	0.341*
*Weather-sensitivity * rain*				
Less-weather-sensitive group			0.118	-0.295
Less-rain-sensitive group			0.334	-0.190
Wind, no wind as ref.				
Light tailwind		0.392***	0.430***	0.439***
Light crosswind		-0.043***	-0.093***	-0.070***
Light headwind		-0.509***	-0.511***	-0.501***
Strong tailwind		0.767***	0.828***	0.878***
Strong crosswind		-0.046**	-0.098***	-0.088***
Strong headwind		-1.004***	-1.046***	-1.032***
Shelter from wind upstream		-1.741***	-1.729***	-1.141***
*Shelter * wind*				
Light tailwind			-0.569***	-0.542***
Light crosswind			0.484***	0.367***
Light headwind			0.013	0.082***
Strong tailwind			-0.900***	-0.935***
Strong crosswind			0.511***	0.472***
Strong headwind			0.579***	0.615***

Land-use, built-up area as ref.				
Semi-built-up area				0.519***
Transport use area				0.057***
Industry use area				0.317***
Nature area				0.826***
Bike lane, residential road as ref.				
Pedestrian areas				-1.041***
Bike street				0.500***
Bike track				0.349***
Bike path along road				0.181***
Solitary bike path				-0.197***
Bridge/tunnel, regular road as ref.				
Tunnel				0.840***
Bridge				-1.876***
Intersection, non-intersection as ref.				
Roundabout				-2.481***
Inter. without traffic lights				-2.651***
Inter. with traffic lights				-7.318***
Before/after intersection, others as ref.				
Before Inter. without traffic lights				-0.143***
Before Inter. with traffic lights				-1.688***
After Inter. without traffic lights				-1.580***
After Inter. with traffic lights				-3.115***
Before/after turn, others as ref.				
Before right turn				-1.733***
Before left turn				-1.801***
After right turn				-4.021***
After left turn				-3.981***
Slope, flat road as ref.				
Downhill				-0.190***
Uphill				-2.584***
Constants	18.441***	18.516***	18.518***	18.371***
Random intercept				
Cyclist variance	7.250	7.051	7.054	6.148
Trip variance	5.200	4.882	4.879	4.515
Tracking point residual variance	14.047	13.842	13.834	11.596
Model fit				
LL	-14513010	-14472792	-144713319	-14010022

5.4.4.2 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 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 0.917 km/h, and similarly, the occurrence of ice decreases speed by 0.510 km/h. Twilight and darkness, meaning limited visibility, decrease cycling speed by 0.257 km/h and 0.134 km/h compared to daylight. Unexpectedly, fog, which also reduces visibility, increases speed by 0.199 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 shows that shelter mitigates the impact of wind by reducing wind speed. Specifically, while strong and light headwinds reduce speed by 1 and 0.5 km/h respectively, full shelter decreases their negative effect by 0.6 km/h and 0.1 km/h respectively. Moreover, the positive effects of tailwinds are even completely removed by full shelter. Remarkably, light and strong crosswinds reduce speed minimally, and full shelter reverses their effects to increasing speed by around 0.3 (-0.07+0.367) and 0.4 (-0.088+0.472) km/h respectively.

The comfort level of cyclists is related to temperature, humidity and rain. A cold weather condition (< 10 ℃) reduces cycling speed, while moist air increases cycling speed, but their effects are minimal. The effect of rain is insignificant in Model 2 and Model 3 but becomes significantly positive at 0.341 km/h in the Full model.

Unexpectedly, different weather-sensitivity groups do not significantly vary in cycling speed. In addition, the influence of rain does not vary across groups.

5.4.4.3 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 and bike paths along main 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 industry use areas, while transport use areas hardly influence 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 hours, increase speed. The trip length minimally increases speed.

5.5 Conclusion and Discussion

5.5.1 Discussion

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

5.5.1.1 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. (2012) found hardly 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 considered to reflect cyclists’ physical strength, including speed differences between age groups and genders (e.g., Romanillos & Gutiérrez, 2019). However, we did not find significant speed differences between weather-sensitivity groups, suggesting that weather-sensitivity can be associated with mindset and attitude rather than physical strength. In addition, the influence of rain on cycling speed was not found to vary across sensitivity groups, which further confirms that weather-sensitivity does not rely on cyclists’ physical conditions.

5.5.1.2 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. Due to the risk of slipping or skidding, cyclists tend to slow down for better control over their bicycle movement. This was also found by Shoman et al. (2023). Twilight and darkness decrease cycling speed to a lesser extent, similar to Yan et al. (2024): 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 determines the resistance experienced, thus influencing the required physical effort and speed. However, nearby upwind buildings block wind and provide shelter, reducing the positive influence of tailwinds and mitigating the negative impact of headwinds and crosswinds. 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 influenced more strongly 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 disappears when it reaches 25 ℃, 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).

Cyclists also increase speed to reduce exposure to uncomfortable situations, especially rain. Rain decreases the feels-like temperature and restricts movement with wet clothes and skin. In addition, this influence accumulates with increased exposure to rain. It confirms two Dutch studies (Fietstelweek, 2017; Yan et al., 2024) and a Swiss study (Maurer et al., 2025) but conflicts with a Spanish study (Romanillos & Gutiérrez, 2019). These different findings are probably due to the temperature difference between the countries.

According to 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, although wind alters the resistance cyclists experience during a ride, they tend to maintain their speeds by adjusting their physical effort, especially for light winds.

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, cyclists are influenced by weather throughout the entire trip, whereas they encounter certain infrastructure, such as intersections and turns, only occasionally at specific locations along the route. Therefore, the coefficients of weather components may underestimate their cumulative effect over a full trip.

5.5.2 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 motorised modes can be improved. The focus should be on precipitation (snow, ice and rain), 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., 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 during 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). In addition, cyclists prefer a high speed, or at least want to wait less, to reduce their exposure to rain. This result enhances the need to prioritise cyclists at intersections during the rain, confirming the practice of installing rain sensor-equipped traffic lights in some Dutch cities, like Rotterdam and Groningen (Vial et al., 2023).

Another solution is a cycling navigation system which can provide cyclists with suitable route recommendations based on real-time weather. It considers 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. Also, given the existence of cyclist heterogeneity regarding the influence of weather, it is recommended to provide route suggestions tailored to user preferences. Such a navigation system is especially a 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. It suggests that the mindset of travellers, 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 travellers. Employers can also provide their employees with equipment, such as raincoats, to support cycling.

5.5.3 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 effect of rain on cycling speed, 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.

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, prioritising cyclists at intersections during rain, sufficient streetlights, and 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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Chapter 6: Explaining Patterns of Cycling Speed Stability and Disruption

This chapter is based on the following article:

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6.1 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 as 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.

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 through 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 are 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 handlebar, 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 brings about 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 about cycling speeds have mainly examined its determinants related to cyclists, trips and the environment during rides (Yan et al., 2024). It was 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 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 accelerations at four different road segments, with two segments having consistent bicycle infrastructure (continuous segments) and two segments having changing bicycle infrastructure (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 speeds or desired speeds when they are not influenced by other road users. This free speed depends on driver characteristics and vehicle conditions, meaning that the free-flow speed 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 the ride. Due to disruptions during the ride, cycling speeds are destabilised, and unstable ride segments arise. Therefore, cycling speed stability was analysed for two aspects: (1) the extent that cyclists can maintain a stable speed and (2) the determinants of speed (in)stability. To this end, cycling data was collected by using GPS devices. Tracking points were recorded with their time stamps and locations so the speed per 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 hardly 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. Section 6.3 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 Section 6.4, while a discussion and conclusion are provided in section 6.5.

6.2 Data and Variables

6.2.1 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 handlebar of their private bicycles. Their cycling data are managed and visualised by Civity (a Dutch company) and validated by the Netherlands National Institute for Health and Environment (RIVM). The project is anonymous, without collecting the participants 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 (Figure 6.1).

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 6.3.1) and deleting missing data (see Section 6.2.3), there are 5,672,552 tracking points from 59,928 trips of 505 cyclists.

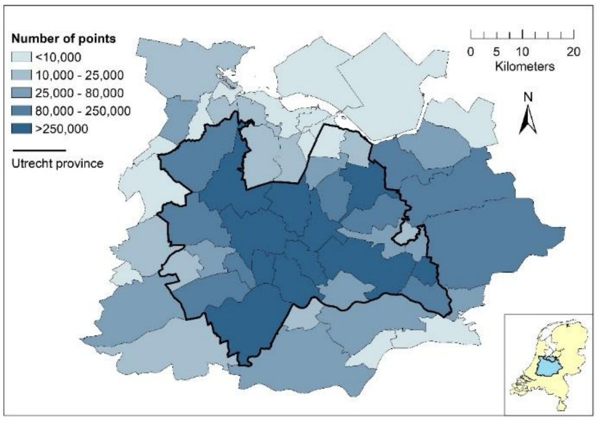


Figure 6.1: The study area and the distribution of tracking points

6.2.2 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 6.3.

6.2.3 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 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 with trip distance and time. Variables for other aspects were also developed. Meanwhile, these variables show a hierarchical structure of trip and point levels (Table 6.1).

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. A tracking point got these attributes from its nearest segment (if accessible by bicycle), while the point was labelled as missing data if there is no bicycle accessible segment within 50 meters of it. Except "before/after turns/intersections", other attributes were derived directly from the Fietsersbond data. A turn was recognised if two road segments formulate an angle over 80°, and right and left turns were distinguished. Points within 30 metres before or after a right/left turn were labelled as "before/after right/left turns". Similarly, points within 30 metres of intersections were recognised as "before/after non-signalised/signalised intersections". There are six bike lane types. The bike path along the road is physically separated from main roads, while bike tracks use road lines or different surfaces to separate from main roads. Solitary bike paths are located away from motorised vehicle roads. Bike streets give permission to cars, but bicycles have the priority. Residential roads have no bike infrastructure, and in pedestrian areas cyclists are usually not allowed to cycle (although they may do).

Table 6.1: 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
	Non-signalised	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 non-signalised	0.9	18.7	35.9
	After signalised	1.0	16.2	17.5
	After non-signalised	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

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 in. The slope of one tracking point was calculated from 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 categorised 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 as its land-use type.

The sunlight condition is a trip-level variable, constant within a trip, depending on the middle 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 period of these three light conditions was based on the location of Utrecht city, which is the centre of the study area and has the biggest percentage of tracking points.

Other road users are 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 with the middle time of the trip. Days of the year 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. The 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 6.1, distinguishing the trip and point levels. For categorical variables, the average speed and the percentage of stable patterns are also reported.

6.2.4 Two-level multinomial logistic model

This analysis estimated multilevel multinomial logistic regression to understand 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 possible 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 cannot get results probably due to the small difference between cyclists. Finally, 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 $\Pr(y_{ij} = k) = \pi_{kij}$. 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

$$\log\left(\frac{\pi_{kij}}{\pi_{1ij}}\right) = \beta_{0k} + \sum_{p=1}^{P} \beta point_{kpij} xpoint_{pij} + \sum_{q=1}^{Q} \beta trip_{kqj} xtrip_{qj} + \mu_{kj} \qquad (6.1)$$

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

$\mu_{kj} \sim N(0, \sigma_u^2)$.

β_{0k} is the intercept in the equation contrasting the k^{th} and 1^{st} 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.

6.3 Speed Stability

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

6.3.1 Speed 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. The reason for segmentation is that 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 previous point by the time difference between these two points. The distance and time difference were derived from the time stamps and locations (longitude and latitude) recorded by 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 continuous tracking points (lasting more than 120 seconds) 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 many different 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 i^{th} segment including data points $y_{(\tau_{i-1}+1):\tau_i}$. Commonly, change points are detected by minimising the algorithm:

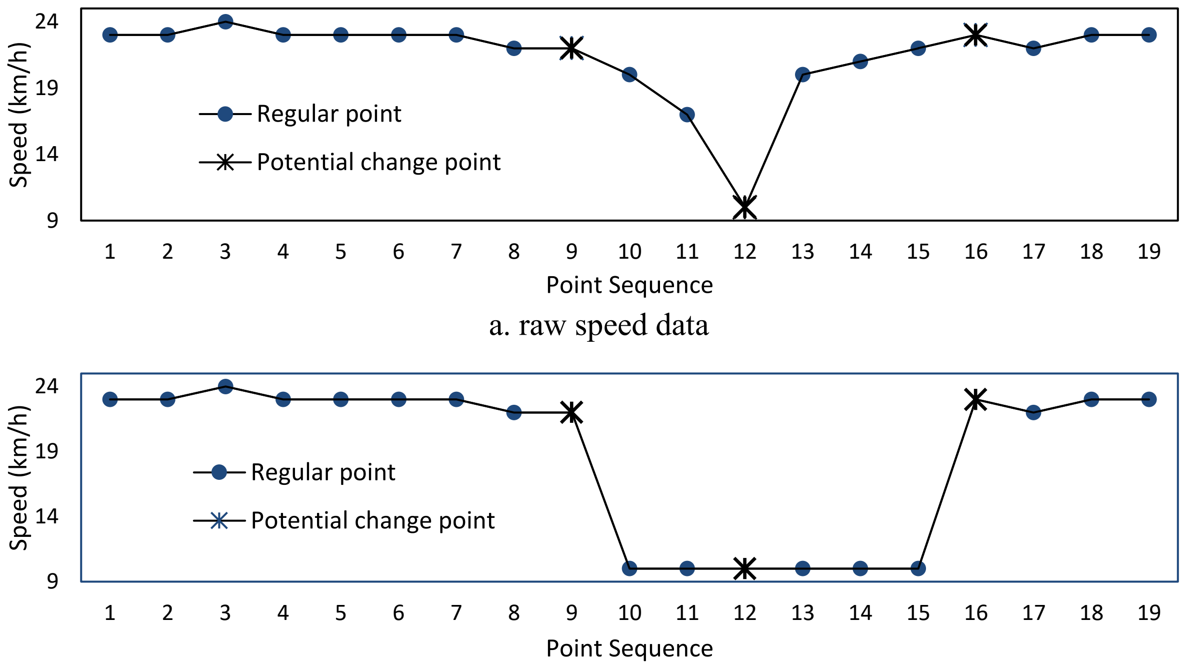
$$\sum_{i=1}^{m+1}\left[C\left(y_{(\tau_{i-1}+1):\tau_i}\right) + \beta\right] \tag{6.2}$$

where C is a cost function of homogeneity of the i^{th} 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 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 Figure 6.2). In addition, cycling speeds during unstable segments can vary significantly.



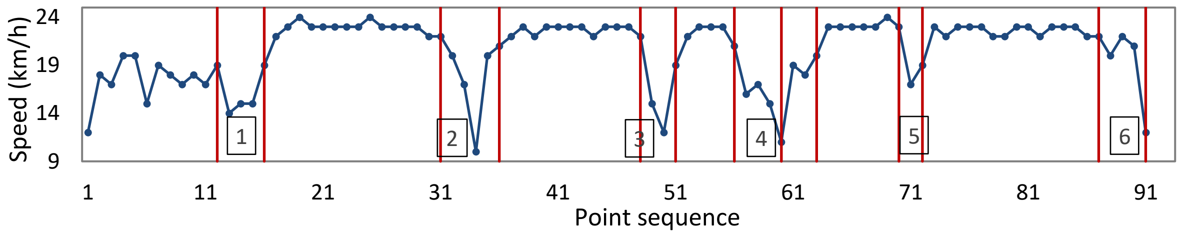
a. raw speed data

b. potential changing speeds at increasing and decreasing phases

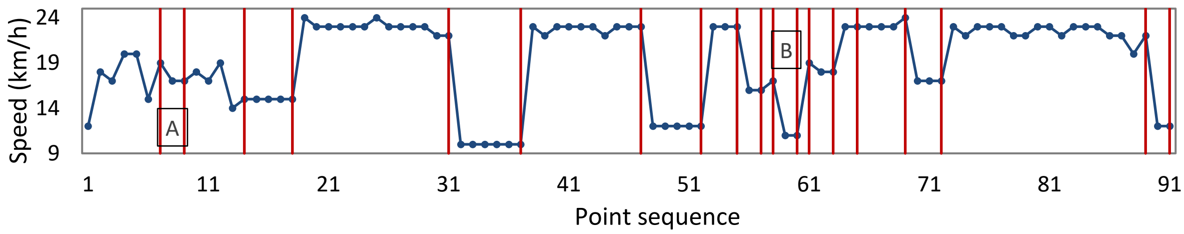
Figure 6.2: An example of raw speed data pre-process

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 Figure 6.2). 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 ignores 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 (6.2). The speed pre-process only aims for better detection of change points, and after segmentation, the raw speed was used for segment classification and the speed stability analysis.

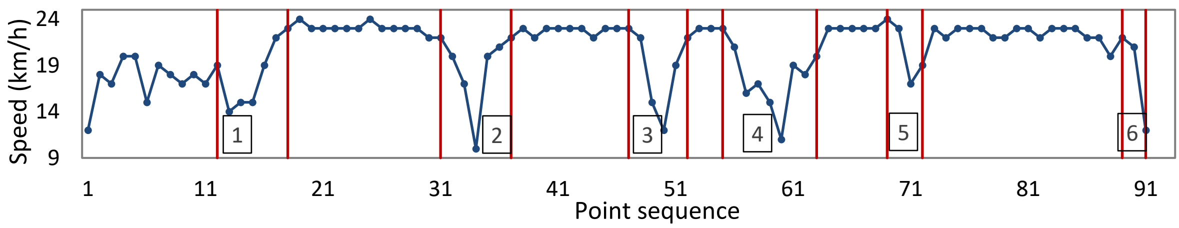
Step (3): CPD (the PELT algorithm) was executed with pre-processed data, which works better than with raw data (Figure 6.3). Figure 6.3a is the result of PELT with the raw speed data, 6.3b shows modified speeds with boundaries of continuously ascending or descending phases as potential change points, and 6.3c 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 position of detected change points, and points on the lines belong to the preceding segments of lines. Compared with the result from the raw data (a and c in Figure 6.3), 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 Figure 6.3), 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-process of speed data improves the performance of the PELT algorithm for our purpose.



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

Figure 6.3: Steps in change point detection

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 Figure 6.3), 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 (Figure 6.4). 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.

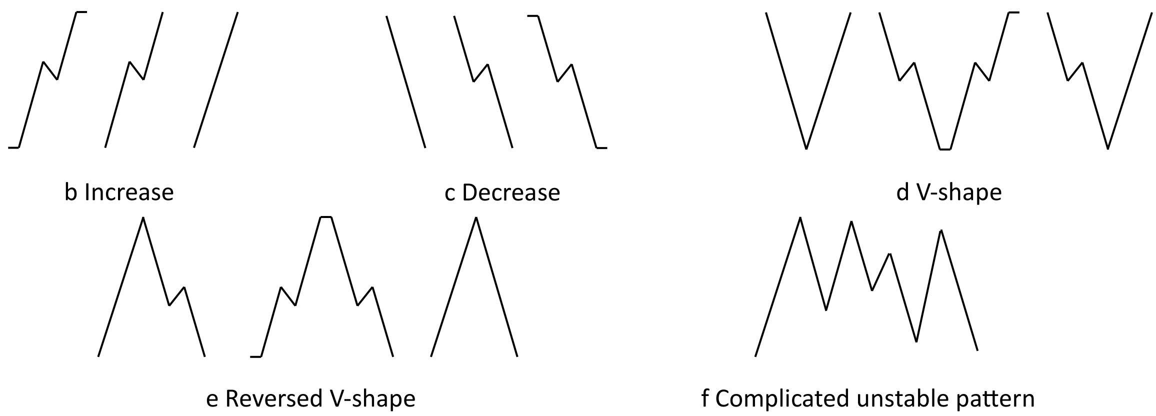


Figure 6.4: The illustration of five unstable patterns

(a) Stable patterns hardly vary in speeds, and are detected with the following rules:

(1) it is not one of the unstable patterns below,

(2) it has at least five points, and

(3) the speed range does not exceed 5 km/h.

(b) Increase-patterns are situations where cycling speeds generally increase (Figure 6.4), based on five rules:

(1) the first point has the lowest speed,

(2) the last point has the highest speed,

(3) the speed difference between the first and last points is not below 3 km/h,

(4) the number of points with an increased speed from its previous point exceeds the number of points with a decreased speed, and

(5) for single points within the segment, the maximum increased speed outstrips the maximum decreased speed.

(c) Decrease-patterns show that cycling speeds generally decrease, which was detected by the reversed rules of the increase-pattern.

(d) V-shape patterns are situations where speeds first decrease and then increase, based on three rules:

(1) the segment has its lowest speed in the middle,

(2) a decrease-pattern is before the point with the lowest speed, and

(3) an increase-pattern follows the lowest-speed point.

(e) Reversed V-shape patterns show increased speeds followed by decreased speeds.

(f) Complicated unstable patterns describe the situation where cycling speeds vary strongly, other than in above-mentioned unstable patterns. Three rules were used:

(1) it is not one of the four simple unstable patterns,

(2) it has at least five points, and

(3) the speed range exceeds 5 km/h.

The speed change of 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 hardly focus 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 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 6.3.2, shows a small growth. 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. As the upper limit of the speed range for the stable pattern, 5 km/h was chosen.

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 keep 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 less 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 short segments otherwise.

6.3.2 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 6.2). 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 a frequency of 26%, and they 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 other 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 unstable segments, except for reversed V-shape segments.

Table 6.2: Descriptive analysis of speed patterns of segments

Segment patterns	Number	Share (%)	Mean speed (km/h)	Std. dev. 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

6.4 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 6.3). Each column shows the results for a contrast between a response unstable pattern and the reference stable pattern. The coefficient is 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 constant the values of all other predictors. For example, the odds of being in the complicated unstable pattern rather than the stable pattern is expected to decrease by 13.0% (1 - 0.870) for trips during weekends than weekdays, and by 16.1% (1 - 0.839) for holidays. This section describes the model results of each factor group, followed by an explanation of the results.

Table 6.3: Estimates from the two-level multinomial logistic model of cycling speed patterns (reference: stable speed pattern)

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
Non-signalised 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 non-signalised intersection	1.540	2.467	1.309	1.902	1.451
Before non-signalised 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	1.954	5.135	1.573	2.250	2.746

intersection					
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

6.4.1 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 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 an 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 pattern). 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.

6.4.2 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 varied speed stability in these bike lane types. Overtaking is a primary interaction involving four simple unstable patterns. Three overtaking strategies have been recognised in car traffic and drivers overtaking bicycles, including flying, accelerative and the piggy backing strategies (Farah et al., 2019). It is reasonable to expect that cyclists have similar overtaking strategies, as observed by Mohammed et al. (2019). For 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 piggy backing 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 metres (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 with road lines from the main road. Although they are narrow, bicycle volume is relatively low (Uijtdewilligen et al., 2022), and cyclists can use the car lanes for overtaking other cyclists, avoiding large speed changes. However, in some cases that 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 for recreational cyclists, which reduces speed differences between cyclists and interactions.

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 area (CROW, 2022; Schepers et al., 2023), prevent 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 this path makes cycling speeds more unstable.

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

6.4.3 Intersections and turns

Intersections and turns strongly destabilise cycling speeds. Cycling at all three kinds of intersections is more likely than at non-interrupted roads to have unstable patterns, especially the V-shape and decrease patterns. Signalised intersections have the largest effects with odd ratios between 2.28 and 12.82, while roundabouts and non-signalised intersections have smaller and similar impacts. Similarly, cycling before and after intersections tends to get in the V-shape pattern, with a stronger effect of signalised intersections. Logically, decrease patterns are more likely to happen before intersections, while increase patterns are frequent after intersections. A close result was found for turns, which cause more unstable speeds, especially the V-shape pattern. 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 possible risks, so cyclists slow down before turns, and speed up after turns. Left turns have slightly larger effects on speed stability than right turns, as traffic is right-handed.

6.4.4 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 in cycling. In addition, pedestrians and cyclists are not fully separate 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 their speed variations.

6.5 Conclusion and Discussion

6.5.1 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 cycling 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.

6.5.2 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 the infrastructure with mixed traffic, such as bike streets, conflicting with many studies which found that cyclists prefer separate bicycle infrastructure 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 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 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 the cycling speed stability. The data used in this study was verified by the Netherlands National Institute for Health and 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 real 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.

6.5.3 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 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 fine 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 of bike lanes with different width and bicycle volumes, it can provide theoretical evidence for optimal widths to ensure comfortable and safe cycling.

Third, a deeper understanding of the influence of other road users is needed, 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 with others, such as during the overtaking situation. 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 lacking, 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 fast 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, time and other factors to match their cycling preferences (Pinjari et al., 2008). For example, cyclists who prefer a smooth cycling (e.g. racing bikes, elderly people) may cycle outside rush hours and at uninterrupted routes with few intersections and lower bicycle volumes. Those who are cautious may prefer separate lanes, which further influence 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 reveal 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 happens at intersections, turns and narrow bike lane types. It is beyond the scope of this study to examine how cyclists experience 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 stability and its implications for planners.

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Chapter 7: Conclusion and Implications

Cycling speed and its stability influence travel time, safety, comfort, and ultimately the attractiveness of cycling compared to other transport modes. Understanding cycling speed has become increasingly necessary, as the introduction of new types of bicycles and infrastructure has increased variation in cycling speeds across cyclists and places. Therefore, this research sheds light on cycling speed, exploring speed variation and speed stability within a trip and examining their determinants. It contributes to a growing need for bicycle-related knowledge in promoting cycling worldwide. Using data from GPS-tracked cycling trips and employing quantitative research methods, specifically multilevel models, this thesis provides rich insights into microscopic speed changes. This chapter summarises the key findings from five studies, discusses the results, and outlines implications and future research directions.

7.1 Main Findings

This research provides answers to five cycling speed-related questions formulated in Section 1.3. These answers have addressed the identified gaps and fulfilled the overarching goal of this research.

7.1.1 What determinants and relationships are involved in determining cycling speed over a trip? (Chapter 2)

The conceptual model of cycling speed

Based on the literature, a conceptual model has been developed. It assumes that cycling speed is embedded in a feedback loop. Cycling speed is directly influenced by individual characteristics (sociodemographics, bicycle ownership, physical condition, attitudes and preferences) and contexts (cycling culture, physical environment, weather and traffic situations). It is also indirectly influenced by these characteristics through other trip choices, including trip purposes, destinations, bicycle mode, route, departure time and within-trip behaviour. Inherently, speed produces effects, including accessibility, health, safety, and well-being, that can reshape cyclists' physical condition and cycling speed-related attitudes both in the short and long term. This change, in turn, is likely to alter future cycling speed and other trip choices for upcoming trips.

In addition, other complex relationships exist between cycling speed-related factors. Cyclists may choose where to live based on their speed-related preferences (residential self-selection). Their trip choices are interdependent. Furthermore, the relationships between trip choices and cycling speed, as well as between cycling speed and its effects, are moderated by individual characteristics and context. This illustrates that cycling speed is a complicated topic, and properly considering these complex relationships can offer insights into cycling speed choice and avoid biased results, such as confounding effects.

7.1.2 What do we know about study designs used to examine the determinants of cycling speed? (Chapter 3)

Studies that examine the determinants of cycling speed can be divided into three study designs distinguished by their data collection strategies. Targeted-segment-based studies (n = 11) observe cycling, often with cameras, along specific road segments. Experiment-based studies (n = 5) invite cyclists to ride at designated routes and investigate in-ride behaviour. Whole-trip-based studies (n = 18) focus on entire rides, mainly tracked by GPS devices or smartphone apps. Most recent studies are whole-trip-based. These study designs differ systematically in data collection techniques, speed measurement, determinants considered, and analytical approaches.

Targeted-segment-based studies examine the effect of specific factors, such as bicycle lane types (Opiela et al., 1980), on cycling speed. Speeds are often calculated aggregately at segments or combinations of segments and time slots. Due to examining a few influential factors, these studies primarily employ descriptive analysis and simple linear regression. Although they can collect a large amount of naturalistic cycling data, they are limited by examining a few factors, without considering the characteristics of cyclists and bicycles, and missing speed variation during a ride. A core challenge for these studies is selecting appropriate data collection locations where their targeted factors should vary, while holding other potential confounders constant.

Experiment-based studies conduct experiments to examine in-ride behaviour, such as phone usage, which is less likely to be systematically observed in the other studies. Although these studies recruit relatively few participants, they can reveal the mechanisms behind the influence.

Whole-trip-based studies can access the characteristics of cyclists, bicycles, and the physical environment, so they are able to examine the influence of these attributes simultaneously. Their sample sizes largely depend on data collection techniques, with standalone GPS devices collecting fewer samples and smartphone apps collecting data from many cyclists. Their speed calculation methods are diverse, including the average trip speed (n = 4), the average speed at route segments (n = 11), and the speed at each tracking point (n = 3). Their advantages include revealing speed variations within trips and simultaneously exploring multiple factors. However, more effort is needed in data collection, speed calculation, and analytical approaches.

7.1.3 How do the characteristics of cyclists, trips and route tracking points influence cycling speed variation within a trip? (Chapter 4)

Speed variance in three levels

Cycling speed varies between cyclists, between trips, and within a trip. Around half (49%) of the speed variance is attributed to factors that vary within trips, 21% is due to heterogeneity between trips, and 30% is due to cyclists.

The influence of cyclist- and trip-level factors

Cyclist characteristics explain the speed variation between cyclists. Women cycle more slowly than men, while age has no influence. Cyclists' attitudes significantly affect speed; those who prefer high speeds cycle faster, and those with a high safety concern cycle more slowly. The self-evaluated health conditions, however, do not influence cycling speed.

Bicycle types significantly impact cycling speed; trips made on electric bicycles have a higher speed than those on city bicycles, and those on sporty bicycles have an even higher pace. Longer trips have a higher cycling speed, but the effect is small.

The influence of tracking-point level factors

The physical environment factors cause speed variations within a trip. Intersections, especially signalised intersections, significantly decrease speed. Speed is also lower after and particularly before intersections/turns. Cycling is faster on all types of bicycle lanes compared to on residential roads without bicycle facilities and pedestrian areas. Surprisingly, cyclists have a higher speed on bicycle streets and bicycle tracks than on physically separated lanes, such as bicycle paths and dedicated bicycle paths. A possible reason is that bicycle streets and bicycle tracks have lower bicycle volumes and larger spaces compared to physically separate lanes. Therefore, on those streets and tracks, cyclists are less influenced by each other, especially during interactions, such as overtaking. Roads involving altitude changes, including tunnels, bridges, uphill and downhill slopes, decrease cycling speed. The influence of land use is intuitive; compared to built-up areas, green and industrial areas have a higher speed, while transport areas decrease cycling speed.

The influence of these factors varies across trips and cyclists. In situations where cyclists need to slow down, such as at intersections, turns, and pedestrian areas, trips with a higher speed decelerate more than those with a lower speed.

7.1.4 How do weather conditions influence cycling speed? What are the roles of cyclist weather-sensitivity and spatial conditions? (Chapter 5)

Three weather-sensitivity groups

Three weather-sensitivity groups were identified in the sample. A weather-sensitive group accounts for a small proportion of cyclists (20.5%), being sensitive to bad weather conditions. A less-weather-sensitive group, being the majority (70.1%), is less influenced by weather. A less-rain-sensitive group (9.4%) is similar to the less-weather-sensitive group but even less sensitive to rain. Compared to the sensitive group, cyclists in the two less sensitive groups tend to make more trips and winter trips.

The direct influence of weather conditions on cycling speed

Weather influences cycling speed through safety, effort required and comfort. Snow and ice occurrence pose safety concerns and strongly decrease cycling speed. Darkness and twilight reduce visibility and slightly lower speed. Fog, which also causes poor visibility, is related to a higher speed, possibly due to lower bicycle volume during the foggy situation. Winds are associated with air resistance and change the required effort during cycling. Tailwinds increase speed, while headwinds and crosswinds decrease cycling speed. The negative effect of headwinds is bigger than the positive effect of tailwinds, and strong winds affect speed more than light winds. Rain influences comfort, and this influence accumulates with the exposure duration. Therefore, cyclists ride faster during rain to reduce their exposure. Temperature and humidity are also related to comfort, and cyclists have a slightly higher speed during warm and humid weather conditions.

Cyclist and geographic heterogeneity

Cyclist heterogeneity was not observed. First, the three groups do not vary significantly in speed, and the influence of rain on cycling speed does not differ across the three groups. Since cycling speed is assumed to be largely determined by physical conditions, the absence of cyclist heterogeneity in cycling speed suggests that mindset, rather than physical conditions, influences people's weather sensitivity.

Geographic heterogeneity was explored by examining the relationships between cycling speed, winds, and building-induced wind shelter as an example. Such shelter reduces the positive influence of tailwinds and mitigates the negative impact of headwinds and crosswinds, illustrating the existence of geographic heterogeneity.

7.1.5 What are the patterns of cycling speed stability and disruption, and their determinants? (Chapter 6)

Speed stability patterns

A combination of a change point detection method and a rule-based algorithm identified one stable speed pattern and five unstable speed patterns: increase, decrease, V-shape (speed decrease followed by increase), reversed V-shape (speed increase followed by decrease) and complicated unstable (frequent speed fluctuation) patterns, from bicycle trips.

Stable segments account for nearly half of the total distance and travel time. Among five unstable patterns, the V-shape is the most frequent, covering 15.9% of the trip distance and 18.3% of the duration, respectively. Complicated unstable patterns represent a relatively smaller proportion compared to the V-shape, while the reversed V-shape occurs infrequently. The percentages for increase and decrease patterns are even smaller. Stable patterns exhibit higher speed and lower speed variability than unstable patterns. This illustrates that daily cycling involves considerable speed instability, which results in increased travel time and greater physical effort.

Determinants of speed stability patterns

Speed stability is influenced by (1) cyclist and bicycle characteristics, (2) bicycle infrastructure, (3) ambient environments, and (4) interactions with other road users. Cyclist and bicycle information was unknown in the dataset, and we used the average trip speed to represent the ability of cyclists and bicycles in cycling. The results show that a faster trip tends to exhibit more unstable patterns, but this effect is relatively small.

Bicycle infrastructure plays an important role in maintaining speed stability. Intersections heavily destabilise cycling speed, causing especially more V-patterns, and signalised intersections have stronger effects than unsignalised intersections and roundabouts. Cycling speed is also unstable on route segments before and after intersections/turns. Decrease patterns occur more frequently before them, while increase patterns are more likely to take place after them. Cycling on roads with gradient changes, such as bridges and tunnels, tends to be unstable. Interestingly, cycling speed is stable on bicycle streets and bicycle tracks but unstable on physically separated and solitary bicycle paths, likely due to differences in bicycle volume and user groups.

Ambient environments include land use and sunlight conditions. Compared to built-up areas, cycling speed is much more stable in green areas and slightly stable in semi-built-up areas and areas used for industry and transportation. Insufficient sunlight conditions, namely during twilight and night, lead to more stable cycling, as cyclists ride cautiously with less speed variation to avoid accidents.

It is assumed that cyclists tend to have unstable speeds when interacting with other road users. However, interactions were not observed from the dataset and cannot be directly examined in our studies. We used two temporal factors, including days of the year (weekdays, weekends and holidays) and peak-hour trips, to represent the possibility that a cyclist interacts with other road users. On weekends and particularly on national holidays, cycling/motorised traffic density is relatively low and more widely spread over the day, and cyclists interact less with other road users, resulting in more stable speeds. Compared to off-peak hours, morning peak hours result in more stable cycling, while evening peak hours show no difference. A possible reason is that, in the morning, commuting is the most frequent reason for cycling, and then cyclists tend to cycle steadily and fast. During evening peak hours, mixed purposes among cyclists lead to a similar possibility of interactions as during off-peak hours.

7.2 Discussions

In this section, we discuss the importance of cycling speed (7.2.1), the determinants of cycling speed variation and stability (7.2.2), cyclists' heterogeneity in speed (7.2.3), and the generalisability of these results (7.2.4).

7.2.1 The importance of cycling speed

An ever-increasing cycling speed is not the final goal of a bicycle network. Instead, safety, comfort and attractiveness are the primary objectives emphasised in bicycle network design guidance and development strategies (e.g., DCE, 2022; Küster, 2024). Especially, cycling speed is associated with bicycle accident rates and severity (Schepers et al., 2017), and recently introduced fat bikes in the Netherlands have sparked more concerns about speeding behaviour.

However, speed remains important, as both demand and supply trends show higher speeds. The most direct evidence is the rising number of electric bicycles purchased and used by cyclists. Electric bicycles, allowing faster cycling, accounted for 48% of new bicycle sales in the Netherlands in 2024 (Hackmann, 2025), up from around 30% in 2016 (Harms & Kansen, 2018). The questionnaire results (Chapter 4) show that 70% of participants try to maintain a high pace. Meanwhile, new bicycle infrastructure is introduced to promote fast and smooth cycling, such as bicycle highways (Rayaprolu et al., 2018). This trend is stimulated not only by shorter travel time but also by safety, comfort, and attractiveness.

A bicycle network that promotes smooth cycling at an acceptable speed with minimal speed fluctuations can reduce safety risks. Bicycles require a minimum speed to maintain motion stability, such as 4.3 m/s (15.5 km/h) (Schwab & Meijaard, 2013). Cycling below this speed increases the required physical effort to maintain motion stability and the risk of falling and getting injuries (Twisk et al., 2017). Cycling speed instability results in frequent dismounting and mounting, which can lead to accidents, especially for vulnerable people, like senior cyclists (SWOV, 2023). In addition, frequent speed fluctuations reduce comfort and attractiveness due to extra effort for reacceleration (Joo et al., 2015). Cycling promotion strategies also reflect this by aiming to reduce stops and turns (Küster, 2024).

Correspondingly, this thesis does not emphasise an ever-increasing speed but rather investigates the situations and road conditions that influence cycling speed and its stability. This knowledge helps policymakers reduce unnecessary speed losses for smooth cycling.

7.2.2 The determinants of cycling speed variation and stability

Theoretically, this study contributes to research on microscopic cycling speeds by examining the determinants of speed variation and stability during a ride. This is a research gap, as speed is often measured in aggregate or as an average. Understanding speed variations is necessary for accurate cycling models (Castro et al., 2022; Flügel et al., 2017; Romanillos & Gutiérrez, 2019). The findings show that speeds vary significantly during a ride, highlighting the necessity of such an exploration.

According to traffic flow theory, cycling speed variation is expected to be influenced by the characteristics of cyclists, bicycles, bicycle traffic, roads and the ambient environment (Belikhov et al., 2025; Hoogendoorn, 2005). Three empirical chapters examine various factors: cyclist characteristics, including preferences, and bicycle types in Chapter 4; bicycle infrastructure, land use, and light conditions in all three chapters; and weather conditions in Chapter 5. Overall, these results illustrate how and to what extent cycling speed varies due to the characteristics of cyclists, trips and routes.

Nevertheless, this thesis does not collect real-time traffic data and cannot directly examine the related factors, including bicycle density or interactions with other road users. Chapters 4 and 6 use temporal variables, namely the day of the year (i.e., weekdays, weekends, and holidays) and time of day (i.e., peak hours and off-peak hours), as proxies for traffic volume. Although these variables are associated with traffic conditions, they cannot fully reflect actual situations, and more direct investigations are needed.

7.2.3 Cyclists' heterogeneity in speed

Humans are inherently heterogeneous, and studying cyclist heterogeneity in speed helps researchers develop more comprehensive theories and better understand causal mechanisms (Bryan et al., 2021). Existing studies have mainly focused on gender and bicycle types (e.g., Schleinitz et al., 2017).

This thesis explores heterogeneity throughout the three empirical studies. Multilevel models are estimated to examine speed differences between cyclists and between trips. Chapter 4 introduces random slopes to examine how the influence of certain factors, such as intersections, differs across cyclists and trips. Chapter 5 identifies three cyclist groups with varying weather sensitivity and explores their different reactions to weather conditions. Chapter 6 uses the average trip speed to represent cyclist/trip characteristics and tests its influence on speed stability. These analyses enhance our understanding of cyclist heterogeneity and inform more precise policies.

The results illustrate that cyclists differ in speed, and this difference increases with the use of electric and sporty bicycles. Results from motorised traffic show that speed differences between vehicles increase accident rates and severity (Choudhary et al., 2018). Similar effects are expected among cyclists, so increased speed differences are likely to exacerbate cycling safety concerns. This influence is greater for vulnerable cyclists, who have a higher risk of being involved in accidents and getting injured than strong cyclists (Johnson et al., 2023). This emphasises the need for further investigation into cyclist heterogeneity, its influences and potential policy measures.

Cyclists with higher speeds experience greater speed losses in locations requiring deceleration, such as intersections and turns. In addition, they tend to be more unstable at speeds. This reveals a challenge in current bicycle systems, where people pursue higher cycling speeds, for example, by using electric bicycles, but infrastructure and traffic conditions often delay and destabilise their motion. Two potential challenges arise: first, people cannot fully utilise their advanced bicycles and physical strength, reducing their cycling-related satisfaction; second, these cyclists are subject to safety issues due to high and unstable speeds (Frendo, 2010; Schepers et al., 2017). These results correspond to the discussion about extra lanes for faster cyclists and support the current practice of bicycle highways (Rayaprolu et al., 2018).

7.2.4 The generalisability of the findings

The generalisability of quantitative research to the full population from which it is sampled depends on the sample's representation, and theoretically, generalisability can only be applied to this target population (Borgstede & Scholz, 2021; Polit & Beck, 2010). Correspondingly, this section discusses (1) the representation of the samples and (2) the transferability of the findings in the Netherlands to other locations.

In general, the samples in this thesis cannot fully represent the Dutch population, especially those in Chapter 4; however, the results are trustworthy. The participants in Chapter 4 are relatives and friends of three master students, overrepresenting students with limited car access. Chapters 5 and 6 use the Sniffer bike dataset. This project requires participants to install a sensor kit with a GPS function on their bicycles, so it can be expected that participants have a positive attitude towards cycling and lower privacy concerns. Consequently, the absolute effects of determinants on cycling speed and stability, as derived from the current datasets, may differ from those in the overall cyclist population. However, speed choice strategies among cyclists are similar in daily cycling, such as deceleration at intersections and turns, and cycling faster when commuting. This suggests that the direction and relative magnitude of effects are reliable. Consistent findings across the three empirical studies further support the robustness of the results.

However, the unique cycling culture in the Netherlands limits the direct transferability of the findings to other places, especially car-dependent countries. The Netherlands has good bicycle infrastructure, flat landscapes, cycling-friendly traffic rules, high bicycle modal share, and strong individual cycling awareness, which together shape a unique cycling culture (Te Brömmelstroet et al., 2020), including cycling speed. Especially, certain bicycle infrastructure types, like bicycle streets (Bruno, 2020), hardly exist elsewhere. Some context-specific results, like high and stable speeds on bicycle streets and cyclists' lower sensitivity to bad weather, differ even from nearby countries (Hudde, 2023). Therefore, transferring these findings requires understanding the underlying logic and adapting it to local environmental and cultural conditions.

7.3 Contributions

This thesis advances the understanding of cycling speed variation and stability through theoretical, methodological and empirical contributions. Theoretically, a conceptual model is developed to capture the relevant factors and relationships related to cycling speed. Based on this model, the influence of a wide range of determinants, including cyclists (socio-demographics and preferences), trips (bicycle types, departure time and trip purposes), weather conditions, and the built environment (land use and bicycle infrastructure), on cycling speed at tracking points is simultaneously examined. This explains the intra-trip speed variation. In addition, cyclist heterogeneity is investigated by including random intercepts into the regression model and by classifying weather-sensitivity groups. Furthermore, the concept of speed stability is proposed for the first time, introducing a new dimension for evaluating cycling performance.

Methodologically, three empirical studies estimate multilevel models to account for dependence among observations due to the nested data structure (cyclists, trips, and tracking points), thereby reducing estimation bias. To explore cycling speed stability, a novel combination of Change Point Detection and rule-based algorithms is developed to identify stable segments and unstable segments with five distinct patterns from cycling trips. This method could be applied to other studies which detect changes within time series data.

Empirically, this thesis provides new evidence on cycling speed variation and stability. It quantifies the influence of cyclist, trip, weather, and built environment factors on speed at three levels (cyclists, trips, and tracking points). It also introduces empirical insights into speed stability by identifying patterns of stable and unstable segments within rides using large-scale GPS tracking data. These findings enrich the understanding of cycling behaviour and the performance of different types of bicycle infrastructure.

7.4 Implications for Practice

The findings of this thesis have practical implications from two perspectives. On the one hand, they can support urban and infrastructure planning and maintenance to promote smooth cycling speeds and mitigate the negative effects of adverse weather conditions. On the other hand, they provide a basis for developing cycling navigation systems that offer route recommendations tailored to cyclists' preferred speeds.

Urban and infrastructure planning could pay more attention to intersections and bike lanes, as they significantly impact cycling speed. Intelligent traffic light systems can be installed at intersections where cyclists experience substantial speed losses. Providing additional space for cyclists at intensively used road segments, such as those along main roads, can reduce the number and influence of interactions between cyclists. In addition, developing fast routes, for example by connecting bicycle streets, could allow faster cyclists to ride at their preferred speeds, partially addressing the problem that they are delayed more in the current cycling network. Together, these strategies enable relatively fast and stable cycling speeds, making cycling more competitive with other modes of transport.

By mitigating the negative effects of bad weather on cycling speed, the issues related to safety, effort and comfort experienced by cyclists can be partially alleviated, and an acceptable travel time could be achieved. The focus should be on precipitation (snow, ice and rain), darkness and wind, which have relatively strong effects. To keep bicycle facilities safe and accessible, it is essential to the timely removal of snow, ice, and leaves from bicycle infrastructure (Chen et al., 2018). Installing automatic street lighting (which is becoming cheaper due to LED lights), especially in areas with complex and busy traffic situations, can help maintain sufficient visibility. For roads exposed to strong wind or wind tunnel effects, trees and other vegetation are a good option to reduce wind speed (Hefny Salim et al., 2015). In addition, cyclists prefer to minimise their exposure to rain, which reinforces the importance of prioritising cyclists at intersections during rainfall. This confirms existing practices in some Dutch cities, like Rotterdam and Groningen, where rain sensor-equipped traffic lights have been installed (Vial et al., 2023). These solutions help reduce speed losses due to bad weather conditions and maintain the competitiveness of cycling.

Cycling navigation systems could also be developed with the results of this thesis. Based on comprehensive knowledge about the relationships between cycling speed, infrastructure, and weather, such systems can (1) provide route suggestions tailored to user preferences for cycling speed and speed stability, and (2) recommend routes that consider route distance and the shelter effect of route attributes under real-time weather conditions, such as rain or wind. In this way, cycling navigation systems can help cyclists make more effective use of available infrastructure.

7.5 Future Research Directions

The literature study in Chapter 2 proposed nine research directions, and three of them had been partially addressed in the empirical studies. Chapter 3 explored speed variation during a trip, focusing on the characteristics of cyclists, bicycles and bicycle infrastructure, by estimating multilevel linear models. Chapter 4 further examined the influence of factors that vary over time, using weather conditions as an example. Chapter 5 focused on speed stability. The remaining directions are still highly relevant. Rather than repeating all of them, this section highlights three key avenues for future work.

First, cyclists' perceptions of speed and its stability require detailed exploration. Theoretically, cycling speed is related to travel time, safety and the attractiveness of cycling, but how cyclists evaluate these effects of speed has hardly been examined. A limited number of studies illustrate that cyclists are dissatisfied with unstable speeds (Joo et al., 2015) and substantial delays (Plazier et al., 2017), while direct evidence remains limited. This topic is important because it highlights the significance of cycling-related studies.

Second, the effect of bicycle traffic (volume, density, and speed) on individual speed and its stability requires further investigation. According to the concept of free-flow speed, the speed variations of an individual cyclist are highly related to the surrounding bicycle traffic conditions. Several existing studies have examined the bicycle flow speed (e.g., Jin et al., 2017), but the relationships between bicycle traffic and individual speed are unclear. Bicycle traffic conditions vary across places, and this can result in different cycling speeds even with the same bicycle infrastructure. Exploring this topic can reveal the specific challenges cyclists face in various traffic situations and help design and arrange bicycle infrastructure within a region to accommodate cyclists and bicycle flows.

Third, it is recommended to investigate strategies to promote an inclusive bicycle network that accommodates both user diversity and speed differences. Cycling is becoming increasingly diverse, due to the introduction of various bicycles and a wide range of cycling purposes. In addition, other micromobility modes, such as roller skates, also make use of bicycle infrastructure. This results in diverse speeds on bicycle networks and poses challenges, such as safety and efficiency issues, for the current bicycle system. Gerike et al. (2022, p. 78) indicated that "current and potential future cyclists are in the focus of cycle network planning", and this focus could be expanded to include all users and their speeds. An inclusive bicycle network, on the one hand, can enable all users to move smoothly at their preferred speed and, of course, legally. On the other hand, it is relevant to the safety of all users. Increasing speed differences between users raises safety concerns, particularly for vulnerable users. Higher overall speeds and a growing share of faster users worsen these risks by increasing interactions between users. To avoid safety issues, vulnerable people may avoid specific routes or micromobility modes. Therefore, bicycle network design should consider the needs of slow users by reducing the negative consequences of speed differences and providing a safe environment. Although the need for an inclusive bicycle network is increasingly recognised, it remains unclear how this aim can be achieved.

7.6 Conclusions

Cycling speed and its stability are assumed to influence the attractiveness of cycling as a transport mode; however, they have not been studied comprehensively. This thesis sets out to explore cycling speed, speed stability and their determinants (the characteristics of cyclists, bicycles, physical environment and context). It finds substantial heterogeneity in cycling speeds both between cyclists and between trips, while the major speed variation occurs within a ride. Intersections and turns cause significant speed losses and speed instability. Surprisingly, bicycle streets and on-road bicycle tracks perform better in speed and stability than physically separated bicycle infrastructure (regular bicycle paths and solitary bicycle paths). This illustrates that, in addition to the layout of bicycle infrastructure, other factors, such as bicycle densities and volumes, play an important role in shaping speed performance and are highly relevant for bicycle network planning.

Cycling has now established itself as a truly global phenomenon. Alongside this rise, the term micro-mobility has gained attraction, highlighting the growing diversity of two-wheeled transport. This diversity is evident not only in design and purpose but also in the wide range of speeds at which these vehicles operate. For urban and traffic planners, it is high time to recognise and address these differences to ensure safe, efficient, and inclusive mobility systems.

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Hong Yan was born in Datong, China. He completed undergraduate studies in urban planning at Northeast Normal University in Changchun, China. After receiving his bachelor's degree in 2014, he pursued a master's degree in human geography at East China Normal University in Shanghai. Following his graduation, he worked as an engineer at an urban planning company.

Hong later joined Delft University of Technology in the Netherlands to pursue doctoral research in the Transport and Logistics group, where he completed the current dissertation. During his PhD research, Hong focused on cycling behaviour, related to speed and speed stability, both of which are closely related to the competitiveness of cycling as a transport mode. By estimating multilevel models, he examined the extent to which cycling speed and speed stability are influenced by characteristics of cyclists, bicycles, built environment, and weather. His work provides policy insights to promote smooth cycling.

List of publications

Journal articles

1 Yan, H., Maat, K., & van Wee, B. (2024). Cycling speed variation: a multilevel model of characteristics of cyclists, trips and route tracking points. Transportation.

2 Yan, H., Maat, K., & van Wee, B. (2026). Explaining patterns of cycling speed stability and disruption. Transportation Research Part A: Policy and Practice

3 Yan, H., Maat, K., & van Wee, B. Cycling Speed and Weather: Roles of Cyclist Weather-sensitivity, Spatial and Infrastructural Conditions. Under review

Peer-reviewed Conference Contribution

1 Yan, H., Maat, K., & van Wee, B., 2022, June. Explaining cycling speed variation during a trip. In 10th Symposium of the European Association for Research in Transportation (hEART)

2 Yan, H., Maat, K., & van Wee, B., 2022, October. Intra-trip cycling speed variation: spatial and temporal heterogeneity in weather effects. In 6th Annual Meeting of Cycling Research Board (CRBAM22)

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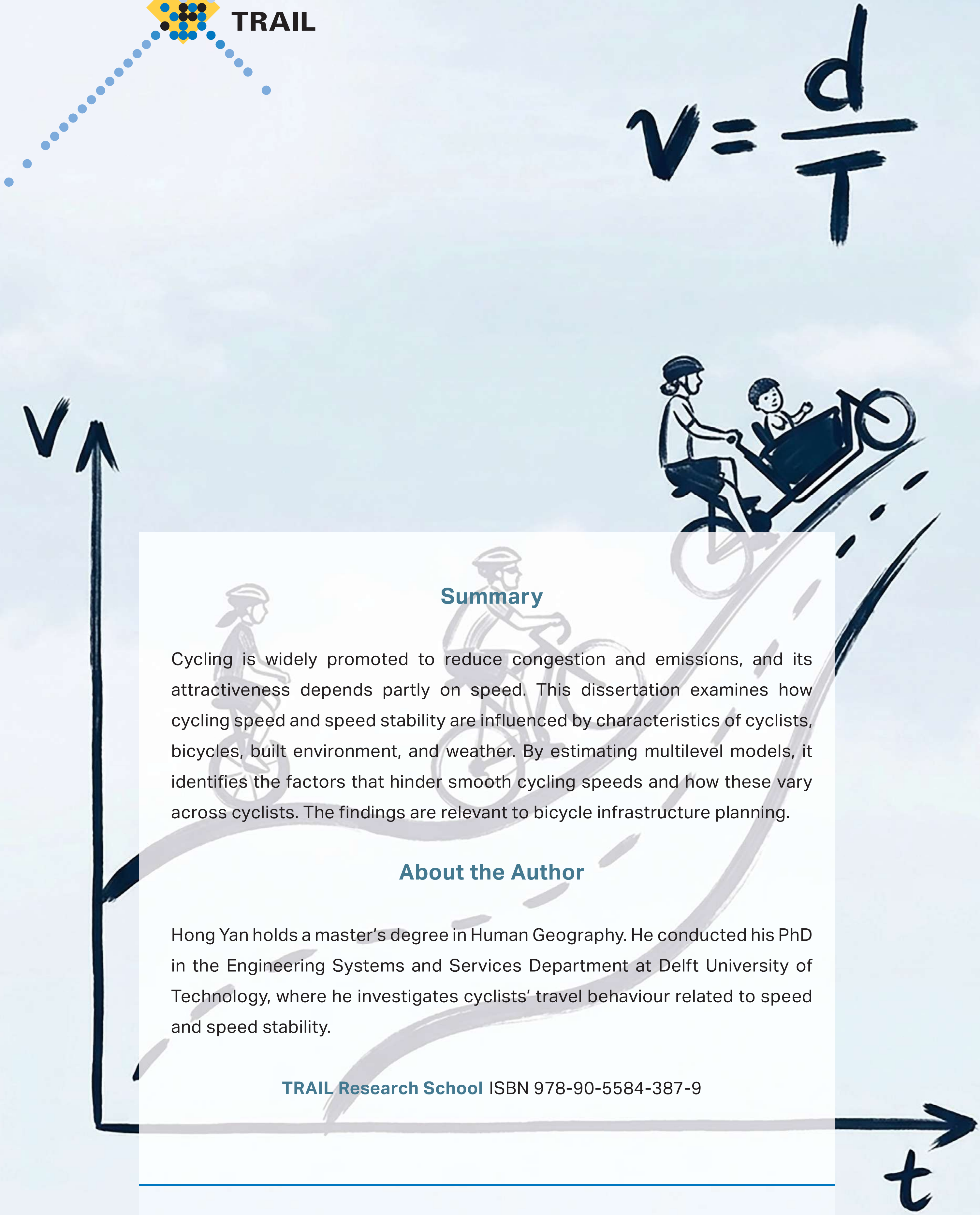

Summary

Cycling is widely promoted to reduce congestion and emissions, and its attractiveness depends partly on speed. This dissertation examines how cycling speed and speed stability are influenced by characteristics of cyclists, bicycles, built environment, and weather. By estimating multilevel models, it identifies the factors that hinder smooth cycling speeds and how these vary across cyclists. The findings are relevant to bicycle infrastructure planning.

About the Author

Hong Yan holds a master's degree in Human Geography. He conducted his PhD in the Engineering Systems and Services Department at Delft University of Technology, where he investigates cyclists' travel behaviour related to speed and speed stability.

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