The effects of speed heterogeneity on cyclists' safety perceptions

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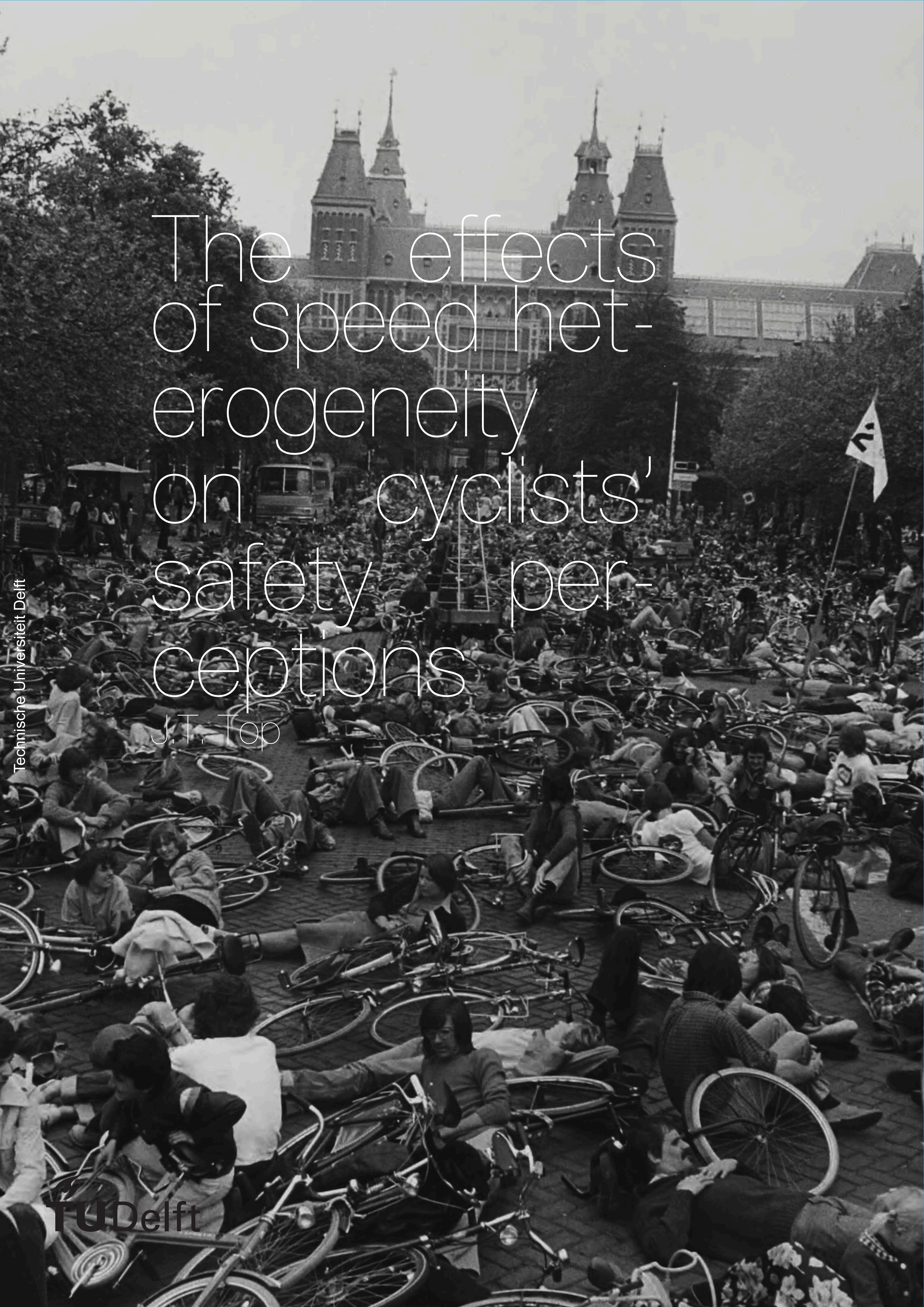

The effects of speed heterogeneity on cyclists' safety perceptions

by

J.T. Top

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Preface

Before you lies the master thesis “Effects of speed heterogeneity on cyclists’ safety perceptions” It has been written to fulfill the graduation requirements of the Master’s Programme Transport, Infrastructure, and Logistics at Delft University of Technology. I was engaged in researching and writing this thesis from May to December 2025.

This report marks the conclusion of an eight-month thesis project and, at the same time, the end of a nine-year academic journey that began when I enrolled as a 17-year-old Aviation student at the Amsterdam University of Applied Sciences. After graduating with my bachelor’s thesis in 2021, I immediately continued with the TIL Premaster at TU Delft, an intensive mathematics-focused program. Although I did not complete the Premaster within the mandatory two-year time frame, I am grateful to the TU Delft student counselors whose support enabled me to still successfully complete the TIL Premaster and start the MSc. programme in December 2023. Now, two years later, I look back on this period with great satisfaction and appreciation.

I am sincerely grateful for the productive collaboration with Arcadis, and in particular for the guidance of my supervisor Matt Bearden. His insights and support were invaluable in shaping this research. I also extend my thanks to Marco Mulder for giving me the opportunity to carry out this research at Arcadis, and my other colleagues at Arcadis for their expertise and discussions on topics such as safety and active mobility.

I would like to thank my academic supervisors at Delft University of Technology, Dr. ir. Dorine Duives and Dr. Jan Anne Annema, for their support, constructive feedback, and expertise throughout this project. Their guidance has significantly enriched both the research process and the final result.

Finally, I want to express my gratitude to my family and friends for their encouragement throughout these years. I also want to thank you, the reader, I hope you find this thesis insightful and engaging.

With this research, I hope to contribute meaningfully to the understanding of subjective cycling safety in Dutch cycle-dense municipalities, and in particular within the municipality of Amsterdam.

J.T. Top
Delft, December 2nd, 2025

Summary

The rapid growth of e-bike usage in the Netherlands has led to increasing speed heterogeneity on cycling lanes. While the increasing popularity of e-bike promotes the bicycle as mode choice, it also raises concerns about its effects on cyclists' perceived safety. These safety and security concerns can act as a barrier for choosing the bicycle as mode choice. To discover the roots of these concerns, this thesis aims to examine to what extend speed differences, within the context of bicycle-to-bicycle interactions in cycle dense environments, shape safety perceptions.

A literature study and complementary discussions with safety experts yielded various factors influencing perceived safety, and these were categorized into four overarching categories: infrastructural attributes, environmental conditions, traffic-related factors, and individual characteristics. Elements such as lane width, lane type, crowding, and sociodemographic differences (including age, gender, and cycling experience) all play significant roles in shaping perceived safety. Despite already existing research in these areas, the specific effect of speed heterogeneity within cyclist-only environments has remained underexplored.

To address this gap, a video-based stated preference survey was developed, enabling respondents to evaluate dynamic overtaking situations under controlled variations in lane configuration, cycling density, lane width, and speed differences. A panel-based mixed logit model was developed to quantify the contribution of each attribute to cyclists' perceived safety. Additional scenario rankings provided complementary insights into how respondents evaluated cycling environments in different scenarios.

The results show that speed heterogeneity has a clear and consistently negative effect on perceived safety. Larger speed differences between cyclists significantly reduce safety perceptions, especially under crowded conditions. Two-directional cycling lanes are generally perceived as less safe than one-way lanes, although this effect is moderated by wider cycling lanes and by cycling experience, where frequent cyclists experience two-way lanes as safer compared to non-cyclists. Interaction effects show that lane type, crowding, and speed differences jointly shape safety perceptions, confirming that the impact of speed heterogeneity on perceived safety is influenced by additional factors.

The study provides several implications for municipal policies. Recommended measures include public awareness campaigns on cycling speeds, accessible reporting platforms for unsafe locations, the introduction of clearly marked slow-cycling zones, and, where space permits, the construction of multi-paced cycling lanes that separates fast and slow cyclist. These interventions aim to improve subjective safety by mitigating the speed heterogeneity between cyclists using a combination of infrastructural and societal measures.

Overall, the thesis provides empirical evidence that speed heterogeneity reduces perceived cycling safety in bicycle-only environments. It contributes to the understanding of cyclist perceptions and provides confirmation regarding the methodological benefits of video-based stated preference experiments for assessing subjective safety. Still, the responses may not fully replicate real-world actions of cyclists since stated preferences are based on hypothetical scenarios. Additionally, real-life location choosing led to minimal variation among similar attribute levels, which may marginally altered results. Future research should examine an extended range of attributes included in discrete choice experiments to see what their impact is of varying speed differences on perceived safety in alternative scenarios. In addition, longitudinal designs should be considered to reveal how users react to improved cycling environments by repeated measures over time.

Contents

List of Figures

List of Tables

Abbreviations

AIC	Akaike Information Criterion
BIC	Bayesian Information Criterion
DCE	Discrete Choice Experiment
DCM	Discrete Choice Model
G40	List of the 41 largest municipalities in the Netherlands
IIA	Independence of Irrelevant Alternatives
i.i.d.	Independent and Identically Distributed
LCCA	Latent Class Cluster Analysis
LL	Log-likelihood
Ministry of I&W	Ministry of Infrastructure and Water Management
ML	Mixed Logit
MNL	Multinomial Logit
PLOC	Perceived Level of Comfort
RP	Revealed Preference
RUM	Random Utility Maximization
SP	Stated Preference
VR	Virtual Reality
WTB	Willingness to Bicycle

1

Introduction

1.1. Background

The increasing popularity of cycling, particularly e-bikes, in the recent year in bicycle-friendly countries such as the Netherlands resulted in an explosive growth in e-bike usage in Dutch cycling networks. Opting for the bicycle as mode choice does not only benefit the health of a person, it is also an environmental friendly way to travel. As explained by Schleinitz et al. (2017) and Uijtdewilligen et al. (2024), compared to conventional bicycles, the electric-driven bicycles reach higher speeds on a regular base. This results in an increase in median cycling speeds, and simultaneously, increasing cycling speed heterogeneity between bicycle lane users. As mentioned by Khan and Mir (2022), the growing popularity of e-bikes and its corresponding higher speeds also raises safety and security concerns, which are identified as barriers for choosing the bicycle as travel mode choice. Additionally, it is also shown that route attributes have a significant effect on perceived safety, implying a direct relationship between perceived safety and route preferences. Furthermore, most cyclists prefer routes they also perceive as safe according to Uijtdewilligen et al. (2024). These safety and security concerns were also acknowledged by Khan and Mir (2022), who identified various factors that shape significant barriers to prevent people in their daily commutes per bicycle.

Lower levels of perceived cycling safety can be derived from varying combinations of infrastructural, environmental, and traffic-related factors. In terms of infrastructural factors, physical separation from motorized traffic, increased lane width, and visual elements such as color-coded surfaces are frequently associated with increased subjective safety, Stülpnagel and Binnig (2022a). However, not only the environmental or infrastructural factors are crucial to understand. A diverse range of sociodemographic factors are to be accounted for to understand which individual characteristics play a significant role in understanding users' safety perceptions Kazemzadeh (2025). Additionally, the increase in speed heterogeneity also tends to have a direct impact on the safety perception of the different bicycle users. SWOV (2022) states that based on theory, it is presumable that cycling becomes less safe by an increase in speed heterogeneity and increasing variation in mass between cycle lane users (i.e. regular bikes, cargo bikes, and e-bikes).

Since low levels of safety perception can lead to cyclists avoiding routes they perceive as less safe or even withholding people from choosing the bicycle as mode choice, a sense of importance arises to explore and examine the levels of perceived safety of persons and what the impact of speed heterogeneity is on safety perceptions. Furthermore, it is also valuable to understand if causes lie differently regarding individuals with various demographic backgrounds and cycling experiences.

Currently, there is still a lot of uncertainty regarding the influence of speed heterogeneity on the subjective safety of cyclists in urban environments, where the focus is placed on bicycle-to-bicycle interaction. Additionally, the problems tends to mostly arise in cities with higher cycling densities where overtaking frequencies are higher compared to rural areas.

As stated in the literature review, few attention has been given to the subjective experience of safety among cyclists sharing space with faster-moving e-bikes. Here, this research closes the gap wherein the effects of speed heterogeneity on perceived safety in urban bicycle-only environments are captured using a video-based approach. Lastly, this research contributes to the level of subjective cycling safety in Dutch municipalities with high levels of cycling density using an distinctive video-based survey methodology.

To understand how urban cyclists perceive their own safety on-route and how possible speed differences might impact this perceived safety, this research aims to examine to what extend speed heterogeneity impacts safety perceptions. In addition, it determines how this impact on perceived safety is influenced by confounding factors, such as cyclists' characteristics, the surrounding infrastructure, and traffic conditions. In the context of these categories, this thesis seeks what trade-offs different cyclists make among these variables. To optimally capture the motions of speed differences, a video-based questionnaire is drafted and shown to respondents. Lastly, this thesis tries to provide Dutch cycling-dense municipalities with pragmatic measures to enhance or increase the perceived safety and consequently positively contribute to a positive image of the bicycle as mode choice.

1.2. Research objectives and questions

The main objective of this research is to gain understandings about what the level of impact is regarding the increasing heterogeneity in terms of cycle speed on safety perception level of cyclists in Dutch cycling dense municipalities, in order to enhance cycling safety-orientated policies accordingly. To answer the objective, the following research questions has been stated:

Main research question: *To what extent does heterogeneity in cycling speeds affects safety perceptions of cyclists in urban dense environments, and how can these effects inform targeted improvements for Dutch municipalities?*

In addition, several sub research questions have been drafted that in conjunction answer the main research question. These are stated below.

Sub question I: How can the effects of speed heterogeneity on perceived cycling safety be measured?

Sub question II: What are the main factors that influence the perception of safety?

Sub question III: What trade-offs between cycling speed heterogeneity and the other variables do cyclists make and can this variance be explained by sociodemographic aspects?

Sub question IV: What measures can Dutch municipalities implement to improve safety perception on cycling lanes?

1.3. Outline

This thesis report has the following structure:

Chapter 1: Introduction introduces the background of this research, states the problem, the main objective and the research questions.

Chapter 2: Literature Review entails a literature review on the relationship between objective and subjective safety and identifies the factors that influence safety perceptions, Additionally, the literature study in this chapter compares various methods that assess the impact of speed heterogeneity of perceived safety, and lastly, the research gap is identified.

Chapter 3: Methodology presents a flowchart regarding the three main phases of the research. Additionally, this chapter states the methodology regarding the way the impact of speed heterogeneity on safety perceptions can be measured. Moreover, the method regarding video-based scenarios is stated. This chapter also contains an explanation on the choices made regarding the questionnaire's design and how these choices were influenced several key factors that were identified throughout the literature study. Lastly, this chapter gives clarification concerning the data collection and what choices were made regarding modeling.

Chapter 4: Analysis & Results describes the questionnaire's sample by looking at its demographics and their responses on several statements. In addition, this chapter yields insights into what trade-offs cyclists make regarding their safety perception by presenting the results of the mixed logit model and the scenario rankings.

Chapter 5: Discussion & Implications contains a thorough discussion on the results' implications, the scientific contribution of this research, and provides municipalities with policy recommendations to improve safety perceptions on cycling lanes. Furthermore, this chapter states the limitations of this research, and presents several recommendations concerning future research.

Chapter 6: Conclusions answers the research questions and states the final conclusions of this research.

2
Literature Review

This chapter presents the literature study that was conducted in the first stage of the research. The literature study consist out of 6 sections. Section 2.1 describes the methodology regarding the literature review. Section 2.2 discusses objective safety and subjective safety and the relationship between both forms of safety. Section 2.3 delves further into the various attributes that impact perceived safety. Section 2.4 analyses and compares the various methods that may be applicable to assess the impact of speed differences on safety perceptions. Section 2.5 provides a discussion regarding the findings of the literature study. In addition, this section identifies the knowledge gap in this area of research and provides several conclusions concerning the literature review. Lastly, Section 2.6 presents the conceptual framework containing all relevant factors that influence the perception of safety during cycling.

2.1. Literature study procedure

For this literature review, the Scopus platform was utilized as primary search engine. This search engine allows conducting aimed searches for the latest available papers on the various themes within the cyclist safety domain. Keywords that were included in the search for relevant papers are displayed in the table below (2.1). In addition to Scopus, a search was performed on relevant published material regarding bicycle safety in the Netherlands on SWOV and the Ministry of I&W related web pages.

Concept groups	Safety, bicycles, infrastructure, risk, perception, speed, methodologies
Keywords	Perceived safety, cyclist perception, cycling lanes, road user behaviour, bike lanes, speed differences, e-bikes, survey, image-based
Truncation	perceived safety AND speed differences AND e-bikes OR perceived safety AND survey AND image-based

Table 2.1: Concept Groups and Keywords during literature search

When examining the scientific papers on Scopus, two extra search criteria were implemented:

- Time frame – Papers must preferable be published within the last 10 years i.e. the period 2015-2025. In case of sources that are fundamental for this research, the publishing year could also originate from years prior to 2015. Hence, the aforementioned time frame is no hard constraint.
- Similar to the temporal constraint, a geographical constraint is implemented. In this case, research papers should geographically wise, preferably, be focused on comparable cycling cultures (e.g., Netherlands, Denmark, Germany). In addition, research concerning urban cycling would be

an additional sub preference. Likewise to the time frame criterion, in case of relevant and meaningful research that originates from other, less well-known cycling countries, exceptions could be made to the geographical constraint.

The additional search criteria yield a well-defined overview of literature. A first iteration of searches was performed through the aforementioned criteria and resulted in a list of 33 papers. All 33 papers were skim-read and by identifying the most relevant scientific articles, additional interrelated papers could be explored using both backwards and forwards snowballing. This resulted in a second iteration wherein all relevant papers were analyzed and used as input for the final literature review. In addition, the utilization of the snowballing methods ensured a deeper dive into the most applicable aspects of a research targeted on perceive safety.

Lastly, a categorization of the papers into several main themes is in place to maintain a clear overview of the various main topics in this research. This extra classification ensured that the overview remained transparent. The categorization also led to an easier identification of areas with potential research gaps and on other areas, wherein extensive research has already been conducted.

2.2. Objective safety versus subjective safety

In the context of transport safety, two types of safety can be distinguished. Objective safety, which is quantitative based (e.g., number of crashes), and subjective (i.e. perceived) safety, which can be explained by how road users experience safety during traveling. Perceived safety is shaped by a combination of individual and contextual factors. Multiple studies state that demographic characteristics such as gender, age, and parental status significantly influence cyclists' safety perceptions Berghoefer and Vollrath (2022) and Stülpnagel and Binnig (2022a). In terms of cyclists groups, female, senior and persons traveling with children tend to perceive greater risk, whereas more experienced cyclists report higher levels of comfort, regardless of the objective safety profile of the infrastructure. In addition, urban context also plays a role. General impressions of city-wide safety were found to explain nearly half of the variance in local route safety ratings Nazemi et al. (2021). On the contrary, objective safety is often assessed via crash data, relating traffic flows with conflict characteristics on the severity of e-bike-vehicle conflicts, or video technology to measure passing distances Khan and Mir (2022) and Götschi et al. (2018). However, these measures may under report near-misses or behavioural risks not captured in official statistics. Furthermore, interventions such as painted buffers or lane markings may improve perceived safety without noticeably changing crash rates, potentially yielding a false sense of security. This false sense indicates the value of acknowledging that overall traffic safety is often a balance between the subjective and objective side of safety.

The relationship between perceived and objective cycling safety is complex and frequently misaligned, with significant implications for infrastructure planning and cyclist behaviour. Features such as physical separation from motorized traffic, increased cycle lane width, and visual elements such as color-coded surfaces are frequently associated with increased subjective safety Stülpnagel and Binnig (2022a). However, these features do not always correspond with a reduction in objectively measured crash risk. For example, certain types of marked cycling lanes are perceived as protective despite offering minimal physical shielding from vehicle conflicts, while some dedicated tracks with statistically lower crash rates are undervalued by users in terms of perceived safety.

When viewing infrastructure and design responses from both safety perspectives, various research papers indicated that specific elements of bicycle lane infrastructure play a role in determining cyclists' safety. Across multiple studies, physically segregated bicycle lanes, for example through curbs or vegetative buffers, emerge as the most effective infrastructure design for enhancing perceived safety. This is particularly among vulnerable groups such as older cyclists Uijtdewilligen et al. (2024). Painted or color-marked lanes also contribute positively to subjective safety. However, their effectiveness diminishes in high-traffic contexts or when physical protection is absent. Lane width appears to be another critical determinant, e.g., smaller lane widths are often associated with discomfort due to reduced maneuverability, while buffered bike lanes, including either painted or physical separation from parked or moving vehicles, yield significantly higher subjective safety rating according to Stülpnagel and Binnig (2022a).

Besides accounting for objective safety in policies, examining subjective safety should be also be examined by policy makers. Nazemi et al. (2021) states that segregated lanes not only rank highest in perceived safety but also increase participants' willingness to bicycle (WTB) across various demographic groups. Hence, an increase in perceived safety leads to an increase in the bicycle as mode choice. Overall, situations occur wherein infrastructure tends to provide a high level of perceived safety, but may provide limited objective protection, and vice versa. These situations present a challenging policy trade-off wherein policy makers should observe both objective and subjective safety.

2.3. Factors determining perceived safety

This section identifies a variety of factors that altogether shape safety perceptions of individuals. The factors are categorized into infrastructural attributes, environmental factors, traffic conditions, and individuals characteristics.

2.3.1. Infrastructural attributes

Bike lanes that were separated from car lanes were perceived as safest according to Nazemi et al. (2021), who evaluated the level of perceived cyclists' safety, and their willingness to bicycle within various infrastructure designs by positioning participants in a bicycle simulator which is based on virtual reality (VR). In addition, Stülpnagel and Binnig (2022a) state that these separated cycling tracks are rated as safer compared to cycling lanes, which in turn are preferred over streets where vehicle-bicycle interaction is high. Moreover, Wang and Akar (2018) identify the importance of intersection design, indicating that treatments such as bicycle boxes, marked crossings, and turn boxes significantly improve perceived safety. Still, the impact of these infrastructural measures varies across cyclist types. These physical separations from car lanes, in combination with wider cycling lanes and marked crossings for cyclists contribute significantly to high levels of safety perception.

Furthermore, in the context of two-lane cycling lanes, where cyclists will also encounter other cyclists from the opposite direction,Kazemzadeh (2025) found that this direction of encounters significantly affected young adults, who perceived meeting other users as more unsafe than overtaking them.

Regarding road surfaces, Berghoefer and Vollrath (2022), who examined individual evaluation criteria that cyclists use to perceive and evaluate certain route attributes, concluded that a combination of crowding in traffic and uneven surfaces for cyclists, such as cobbled stones, were rate as most negative. Furthermore, the color of the road surfaces comes with conflicted statements.Nazemi et al. (2021) indicates that colored roadside and cycling paths were viewed as less safe, whereas Stülpnagel and Binnig (2022a) declared that a colored surface positively impact the perception of safety on cycling lanes. Hence, a correlation is distinguished between the road surface and the level of safety perception of its users. Moreover, Rooij (2021) states that unsafe feelings are primarily caused by other road users' behavior, speed differences, and traffic density, especially on non-separated roads and intersections Besides intersections, roundabouts also contribute to the feeling of cyclists' unsafeness. Affirming this, Kong et al. (2025) focused on e-bike safety at roundabouts, providing insights into how geometry and traffic characteristics affect e-bike-vehicle interactions in the absence of dedicated e-bike lanes. Specifically multi-lane roundabouts increase conflict severity. For these roundabouts, a combination of high traffic levels and increasing speeds negatively influences the level of conflict difficulty with other road users.

2.3.2. Environmental factors

In the context of environmental factors, Campos Ferreira et al. (2022) discuss several factors which influence, among comfort and security, the safety perception pedestrians and cyclists. In this research, it is stated that high values of air and noise pollution, bad weather conditions, slopes and long commuting distances negatively affects the road users' perception. In addition, Campos Ferreira et al. (2022) also found that poor lightning tend and the perception of safety entail a negative correlation.

2.3.3. Traffic factors

Unsafe feelings are primarily caused by other road users' behavior, speed differences, and traffic density, especially on non-separated roads and intersections. These statements are made by de Rooij (2021), who opted for a combined approach of conducting a literature review, analysis of survey data, and semi-structured interviews with residents. In line with this statement, are the findings of Khan and Mir (2022), who state that for regular commuting cyclists, low levels of safety and security act as a major barrier for opting for the bicycle as transport mode. It was found that the main cause of these low levels were nearby high-speed vehicles and the absence of cycling tracks that separate cyclists from (heavy) motorized traffic. Haustein and Møller (2016), who examined the correlation between demographics, driving attitudes, and safety outcomes by conducting a survey among e-bike users, found that the behavior towards other road users, specifically regarding overtaking and speeding, influenced subjective safety and its impact on incidents.

Uijtdewilligen et al. (2024) concluded that high levels of crowding negatively impact route preferences as well as perceived safety. High crowding levels tend to have a negative impact on the preferences of routes and the feeling of safety on cycling infrastructure. The relation between traffic factors and individual variables, such as gender and previous experiences as a cyclist, plays a role in the context of the perceived level of comfort (PLOC). The perceived level varied with different levels of traffic and engineering treatments. Regarding gender, women were more affected by the presence of heavy traffic and more prone to implementations of engineering treatments according to Abadi and Hurwitz (2018).

Lastly, Coughenour et al. (2015) conducted a survey asking 450 residents about which types of infrastructure were perceived as safe and most likely to be used. The outcomes identified infrastructure with minimal vehicle separation was perceived as least safe. The most preferred infrastructure type had understandable signage and clear separation between road users. Furthermore, the option wherein lanes where shared among cyclists and bus traffic were perceived as least safe.

2.3.4. Individual characteristics

Several complementary personal linked variables tend to be influencing the feeling of safety. Behavior plays a role within the domain of individual characteristics, namely risky behaviors include speeding, running red lights, and wrong-way riding tend to have its impact. Behavioral variations are linked to user demographics (e.g., age, gender, patience). Effective prevention includes regulation, education, and infrastructure improvements as stated by Ma et al. (2019). Moreover, riding style and e-bike attitudes influenced perceived safety and incidents. Also, the female gender and an older age were associated with a decrease in subjective safety levels. Almost one-third of the respondents in the research of Haustein and Møller (2016) reported incidents that were unique to e-bikes, often due to misjudgment of speed by others or difficulty controlling speed and balance. Moreover, Uijtdewilligen et al. (2024) concluded that the impact is heavier for older cyclists and women when observing the interaction between crowding and route preferences of cyclists.

In line with the findings of Ma et al. (2019), Kazemzadeh (2025) concluded that women feel less safe in shared spaces compared to men. In addition, Abadi and Hurwitz (2018) found that the previous experiences of cyclists and the effect of gender vary with fluctuating circumstances in the context of traffic and infrastructural factors. Variations in these factors lead to different levels of perceived levels of safety. Furthermore, women gave higher risk ratings than men according to Ayad et al. (2024), who employed a bicycle simulator to test different road segments in a virtual environment.

Regarding cycling experiences, commuters who cycle regularly tend to feel more confident in riskier traffic and infrastructural environments according to Nazemi et al. (2021). In addition, Schepers et al. (2020) expressed that cyclists in regions with less cycling infrastructure (e.g., Brussels and other areas within the federal region of Wallonia) have a greater misperception of risk. These cyclists mainly tend to overestimate its risk. W.P. Vlakveld (2008) supports these findings by stating that factors such as fear and unfamiliarity impact the perception of individual risk. Lastly, Coughenour et al. (2015) revealed that infrastructure preferences varied across demographic groups, which aligns with the finding of the previous studies. Thus, rider characteristics such as age, behavior, and experience levels are among the other variables that form the individual characteristics. These characteristics vary considerably between cyclists, and are partially shaping perceptions of safety.

2.4. Methods to measure safety perceptions

When focusing on possible methodologies to gain insights into the perceived safety of Dutch urban cyclists and the influence of speed differences, various research papers yield useful findings. Herein, several studies on perceived safety have adopted a variety of methodological strategies. These all come with distinct strengths and limitations. Firstly, Costa et al. (2025) present an approach using image-based pairwise comparisons in combination with a deep learning model to assess perceived safety across diverse cycling environments. By incorporating the possibility of tied comparisons, where two environments are perceived as equally safe, the model captures variations in user judgment which might be missed by traditional ranking systems. Although this method shows strong potential for comprehensive perception mapping, its reliance on static imagery and the lack of dynamic traffic limits its value in speed-based cycling conditions.

Image-based survey design has also been studied by Stülpnagel and Binnig (2022a) who underline the benefits of using visuals to capture perceptual judgments in dense urban settings. These surveys reduce the vagueness linked to verbal descriptions of infrastructure. However, as with Costa et al. (2025), the use of static images raises concerns regarding the exclusion of key dynamic elements such as motion and interpersonal interactions. These may significantly influence perceived safety. Video-based assessment studies were also conducted. Jones and Carlson (2003) conducted a car-based video assessment to capture a realistic environment with a focus on overtaking speeds of passing vehicles. The car with the mounted camera would drive at a bicycle average pace to simulate how cyclists perceive passing vehicles. With this method, speed differences between cyclists and passing vehicles are effectively captured. Still, while these methods yield insights into factors belonging to context-specific perceptions, it should be noted that they may require considerable cognitive effort from respondents.

Ma et al. (2019) conducted a comprehensive scoping review of various assessment tools for evaluating the safety and comfort of cycling environments. Their classification distinguishes between subjective and objective measures, and entailed questionnaire survey methods, structural equation models, and binary probability models. Despite this broad range of research tools, the review identifies a lack of standardization and sensitivity to vulnerable user groups, indicating the need for more inclusive and context-specific instruments. Furthermore, Gu et al. (2025) discuss user-centered methods that include a combination of virtual reality and physiological sensors to evaluate bicyclist reactions to infrastructure, and image-based choice tasks to evaluate safety perceptions under varying conditions, such as infrastructural crowding and typology.

Lastly, studies such as Stülpnagel, Petinaud, and Lißner (2022), and Costa et al. (2025) integrate subjective assessments with infrastructural data to assess the relationship between safety perception and a variable cycling environment. To assess this relationship, these studies employed pairwise image-based comparisons of real-world scenarios and reports from crowd-sourced projects respectively. These methods are useful for identifying broad patterns in subjective safety, but seems to be limited in their capacity to model behavioural responses to speed differences between cyclists.

2.5. Identifying the knowledge gap

With regards to perceived versus objective safety, the difference between perceived and objective cycling safety presents a challenge for transportation planning. While design elements such as broad cycling lanes and separation from other traffic can enhance subjective safety, they do not always align with measurable reductions in crash risk. Perceived safety is heavily influenced by demographic factors and contextual perceptions, whereas objective safety relies on quantifiable data, which may overlook near-misses or risk-inducing behaviors. Hence, this mismatch can result in infrastructure that feels safe but offers limited actual protection.

Infrastructure and design interventions seem to play a key role in shaping cyclists' perceived safety. Elements such as lane width, painted buffers, and intersection treatments like bike boxes can further enhance subjective safety. However, their effectiveness can vary depending on traffic conditions and cyclist experience. Rider behavior, psychological factors, and demographic characteristics affect perceptions of safety, particularly among vulnerable users and in suboptimal infrastructure conditions. This emphasizes the need for adaptive infrastructure design and targeted safety interventions to facilitate inclusive cycling lanes wherein subjective safety will be improved. In addition, improving the subjective safety of cyclists tends to increase the willingness to cycle, and is consequently deemed beneficial for cycling as mode choice.

While advancements in image-based surveys have improved scalability and experimental control, these tools often miss crucial contextual factors like motion and interaction. Hence, there remains a need for methodologies that capture the dynamic and interactive nature of cycling safety perception, particularly in the context of increasing speed heterogeneity due to e-bikes. An optional method is the video-based survey, which effectively captures dynamic situations wherein vehicles overtake with different speeds. Another possible method to capture motion in perceived safety is the use of VR-based simulation wherein participants are asked to put on a pair of VR-glasses and sit on a bicycle in a closed environment. Compared to video-based surveys this method seems to be limited since tests are being conducted in a closed environment which insufficiently represents a real-life situation. Compared to image-based surveys, methods such as VR and video-based assessments provide richer insights into real-world perceptions but can be cognitively demanding or resource-intensive. However, a lack of standardized tools and sensitivity to diverse cyclist profiles continues to exist across studies. This stipulates the need for integrative, adaptive methodologies that combine subjective assessments with dynamic environmental data to accurately reflect cyclists' safety perceptions in the context of speed heterogeneity. Thus, video-based surveys tends to possess the highest potential to play a key role in effectively determine safety perceptions regarding varying speed differences and therefore increasing the understanding on how speed heterogeneity influences perceived safety in shared urban cycling environments.

Altogether, while objective speed data and behavioural risk factors have already been well documented, less attention has been given to the subjective experience of safety among cyclists sharing space with faster-moving (e)-bikes. In addition, a challenge remains to select an appropriate method for capturing speed differences within a bicycle-to-bicycle interactions. The lack of previous research reveals a knowledge gap regarding the influence of speed heterogeneity on subjective safety of cyclists in cyclist-only environments. This gap could especially be relevant in densely cycled cities such as Amsterdam, where a variety of bicycle rider types and high bike lane usage create complex traffic situations wherein the interaction between cyclists is deemed crucial for safety perceptions.

2.6. Conceptual framework

The conceptual framework displayed in Figure 2.1 contains the factors from the literature review which influence the level of safety perception during cycling. These factors have been categorized in three main categories, infrastructural attributes, traffic factors, and individual characteristics. The speed heterogeneity attribute is shown as a single attribute to magnify its importance in this research. The arrows in 2.1 indicate the direction of influence. The arrows display that the attributes within all three categories influence the level of impact that speed heterogeneity has on the feeling of safety of an individual.

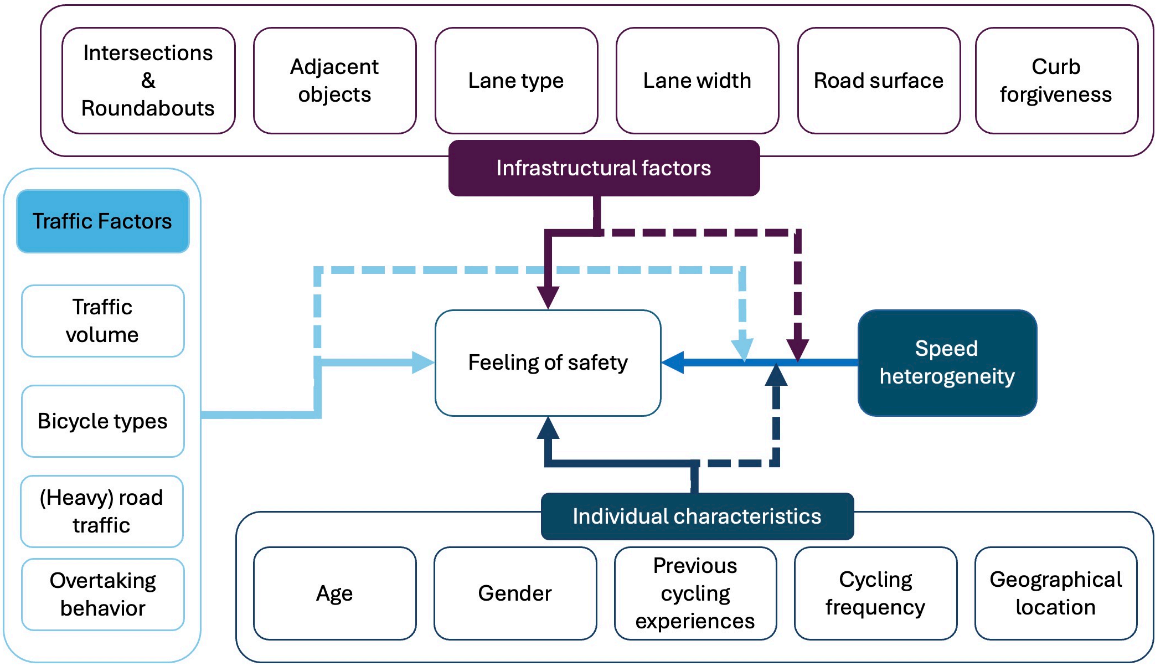


Figure 2.1: Framework of factors influencing the feeling of safety

3

Methodology

In this chapter, all methodological aspects of measuring speed heterogeneity are explained. Section 3.1 provides an overview of the complete research methodology. Section 3.2 explains which attributes from the conceptual framework will be coded as binary and which will be maintained as constant throughout the scenarios of the questionnaire. Section 3.3 describes the location selected for filming. Section 3.4 clarifies the filming setup. Section 3.5 states the method regarding the questionnaire design. Section 3.6 provides the Ngene configuration and its added value to the study. Section 3.7 describes the process regarding data collection. Finally, section 3.8 explain the data analysis processes. In this final section, the mixed logit method is also presented.

3.1. Overview research methodology

To optimally answer the sub-research questions, an approach which combines both qualitative and quantitative data collection techniques has been selected. This approach allows the researcher to gain a comprehensive understanding of the factors influencing safety perception, as well as the underlying demographic, infrastructural, and traffic variables that impact this perception. Figure 3.1 provides an overview of the research stages and is based on the formulated research questions.

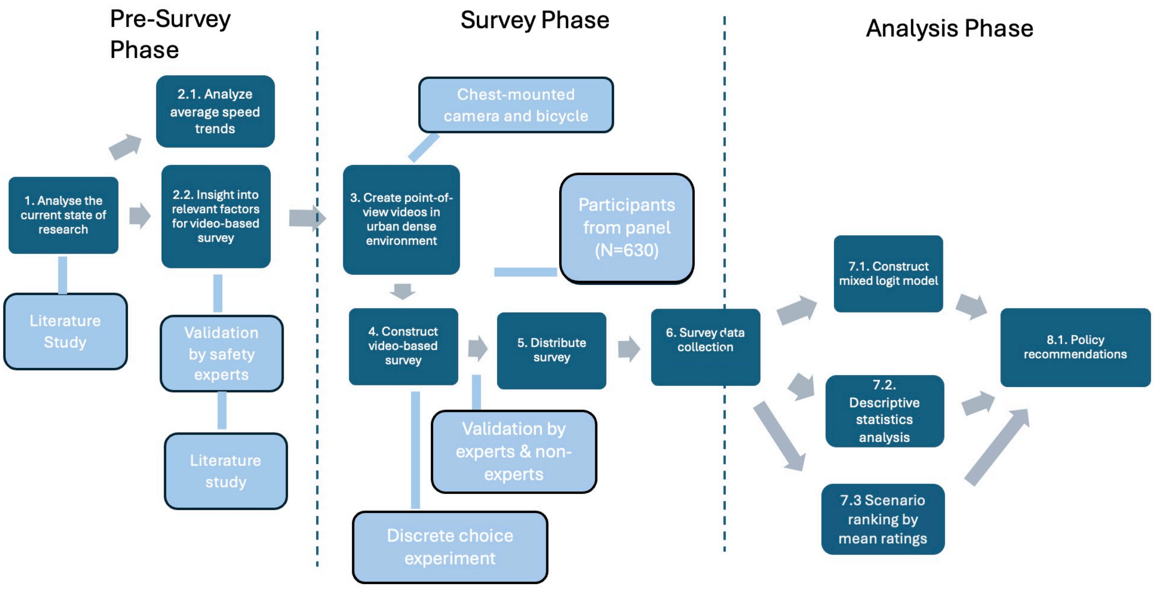


Figure 3.1: Phases of the research

The research is subdivided into three main phases. A pre-survey phase, a survey phase, and an analysis phase. The **pre-survey phase** commenced with an analysis of the current state of studies on perceived safety related subjects. In this phase, sub research question II is answered through literature research, and supplemental informal discussions with in-house safety experts of Arcadis are conducted as validation. Subsequently, trends in average cycling speeds and speed heterogeneity are analyzed to quantitative underline the importance of the impact of speed factors on subjective safety of cyclists.

Discussions with safety experts in the active mobility context are conducted to obtain a form of guidance during the video creation step in the **survey phase**. After the video creation, the material is analyzed, filtered and processed in such a way that it is ready to serve as input for survey. Here, the final part of sub research question II is being answered. Subsequently, a pilot survey is created and shown to 15 respondents with a variation of educational backgrounds so that the pilot survey is reviewed from different perspectives.

Following the collection of the survey results, the **analysis phase** commences. This phase entails analyzing the descriptive statistics regarding the sociodemographic variables and mixed logit modeling to gain insights which effect each factor has on safety perceptions and how these factors influences the effects of cycling speed differences. Here, sub research question III is answered. Based on this analysis, policy recommendations are stated to help Dutch municipalities to enhance their cycling safety policies (sub research question IV).

3.2. Attributes impacting perceived safety

Subjective safety pertains to the individual cyclist and the extent to which this person experiences a sense of comfort during the cycling journey. The literature review indicates that perceived safety is influenced by a range of determinants. These determinants can be grouped into three primary categories: infrastructural attributes, traffic-related factors, and individual characteristics, with an additional category capturing weather-related variables. In order to design a survey in which these attributes are systematically manipulated across different scenarios, it is essential to identify which of them should be treated as key factors and thus be incorporated as varying attributes in the questionnaire, alongside the attribute of speed heterogeneity, and which should be maintained constant across all scenarios.

3.2.1. List of attributes

The attributes list impacting perceived safety is compelled through a twofold approach. Firstly, a literature research is performed to discover these attributes. The literature yielded a first iteration of a list of attributes. Subsequently, this list was shared with two safety experts of Arcadis, who assessed this list, provided feedback, and also proposed additional attributes. Consequently, the outcomes of both iterations were merged and a conceptual framework was constructed. This conceptual framework is shown in Figure 2.1.

With respect to the attribute list, a distinction is made between two-level attributes (binary) and one-level attributes (constants). The latter correspond to attributes that must be held at a fixed level throughout the experiment. The principal challenge lies in preserving all one-level attributes at this exact constant level. When such an experiment is conducted in a virtual environment, the surrounding conditions can be systematically manipulated to ensure that these constant attributes are satisfied. In contrast, an experiment that involves real-world locations, actual individuals, and their associated behaviors introduces substantial complexity in this regard. To address this challenge, a so-called “Mastersheet” is employed, in which all specified attributes are assigned a value for each cycling track that could potentially serve as a location for the scenarios. Because locations primarily differ in their infrastructural characteristics, the Mastersheet is predominantly populated with data pertaining to attributes within this infrastructural category.

As the research focuses on cycling tracks that are physically segregated from motorized traffic, many infrastructure-related attributes typically associated with mixed-traffic cycling facilities are excluded from consideration. Furthermore, cycling streets (Fietsstraat in Dutch) are not incorporated in the study design due to the continuous interaction they entail between motor vehicles and cyclists. With respect to the infrastructural factors, several iterations and discussions were necessary to reach consensus on which characteristics could be treated as invariant across all video recordings.

3.2.2. Fixed infrastructural & traffic attributes

The constant attributes and its fixed values are presented in Table 3.1. Firstly, the cycling infrastructure within the scenarios should not alter straight-line cycling speeds. To satisfy this, any corners or bends should be excluded from the locations. Additionally, since intersections and roundabouts would mean that cyclist might have to stop and yield for other road users, these were also excluded. Moreover, the cycling lanes should not contain any up or downwards inclination that might affect cycling speeds. Furthermore, the cycling track surface is required to be even, asphalt-based, and preferably delineated by a red pavement to ensure that the surface component yields marginal influence on safety perceptions across scenarios.

In the context of attributes pertaining to the cycling lane, curb forgiveness must remain uniformly low across all scenarios. Additionally, the curb forgiveness level is set to *high*, indicating that cyclists can maneuver toward the sidewalk with relative ease, thereby ensuring that participants' safety-related decision-making is not unduly constrained or biased. To facilitate realistic and easily replicable scenario construction on Amsterdam's cycling infrastructure, the left-hand side of the direction of travel is consistently bordered by physical elements such as green spaces, bollards, parked cars, and parked bicycles. In contrast, the right-hand side remains largely unobstructed and typically consists of a curb, an adjacent pedestrian facility, and, in some cases, isolated street posts. To maintain visual and spatial consistency across scenarios, adjacent objects are preferably positioned within 0.5 meters of the cycling track. Finally, because this research focuses exclusively on bicycle–bicycle interactions, the influence of (heavy) motorized traffic must be minimized as much as possible. The presence of tram tracks in proximity to the selected locations is permitted, as the impact of moving trams can be effectively reduced by delaying data collection until a tram has passed.

Attribute	Fixed value
Corners/bends	None present
Intersections or roundabouts	None present
Inclination	None present
Cycling lane surface	Red-marked aphalt-based surface
Curb forgiveness	High forgiveness
Adjacent objects [left]	Signage, trees, parked vehicles & bicycles
Adjacent objects [right]	Sidewalk with occasional pedestrians
Nearest object distance	< 0.5 m
Motorized traffic interaction	Nearby, no direct interaction

Table 3.1: Constant attributes and their fixed values

3.2.3. Fixed weather variables

Environmental conditions, comprising all weather-related variables, are known to influence cyclists' perceived safety. Across all scenarios, these meteorological variables must therefore be held as constant as feasible to minimize confounding effects on respondents' reported feeling of safety. One way to approximate such constancy is to ensure that natural lighting conditions remain similar across all video recordings. Filming during the summer months offers an advantage in this regard, as natural light levels during both peak and off-peak hours remain nearly stable. Under these circumstances, only changes in weather type are likely to alter natural illumination (e.g., rainy and overcast versus sunny and cloudless conditions). Wind speed and direction likewise affect the travel behavior of cyclists. Strong crosswinds or headwinds may unintentionally alter cyclists' speeds and their interactions with other users of the cycling facility. To control for these effects, recordings should be conducted under comparable weather conditions, thereby reducing variability in wind-related influences.

For each filming day and location, location-specific timecards are compiled to record and subsequently validate the values of the relevant weather variables and to assess potential variation among filming days. The weather-related data are obtained from the Weerplaza (2025) weather application. Figure 3.2 presents an example of such a timecard for the Cruqiuskade location on 29 July 2025.

Date and time	29/07/2025 14:20	**Lane type**	**Lane width**
Location - attribute values	**Cruqiuskade**	2-way	220 cm
Traffic attributes	Off peak/peak hour	Off peak hour	
Environmental attributes*	Weather type	Slightly cloudy	
	Temperature	22 degrees Celcius	
	Wind direction & speed	NW 16 km/h	
	No precipation	☑	
	Humidity	47%	

Figure 3.2: Example of a timecard for Cruqiuskade

3.2.4. Multi-level attributes

For a discrete choice experiment (DCE), scenarios can only be constructed when multi-level attributes have been included in the experiment. To assess the weights of the various factors influencing the feeling of safety, the attributes must vary between different values. Corresponding attribute levels should be selected carefully. There is always an optimal scenario with many attributes, attribute levels, alternatives, and the assessment of all interaction effects Molin (2023a). However, when including many attributes and its levels, the research will quickly become too complex for respondents, but also as researcher to interpret and accurately analyze the survey results. Besides, not all scenarios will make sense. Thus, choices and trade-offs must be made. For each binary attribute, the attributes have been carefully compelled to ensure a balance between practicality and reflecting real-life situations on cycling lanes.

To reach an well-grounded number of attributes varying in levels, Louviere, Hensher, and Swait (2000) recommends to maintain the amount of multi-level attributes between 4 and 6 to maintain cognitive manageability during the DCE. Since visual stimuli in the form of videos, which are cognitively exhausting, are shown to the respondents, the number of attributes should be near the lower bound of the before-mentioned range. The selection of a limited amount of attributes will also prevent attribute overload to respondents and ensure accurate answering.

The variance in attribute levels must be displayed in such a way that respondents are able to clearly recognize differences throughout the video recordings. To satisfy this display, locations have been selected accordingly. Hence, it becomes easier for respondents to make trade-offs between the variables while they are being visually stimulated by the video-based discrete choice experiments.

The attributes levels have been determined based on the researcher's own assessment of the importance of attributes for research. This assessment is grounded in both informal discussions with Arcadis' safety experts in conjunction with discussion results with representatives of Fietsersbond, Gemeente Amsterdam, and lastly, the connection within the researcher's direct social network. Adhering to the constraints in terms of cognitive manageability leads to a choice to vary four attributes in two distinct levels. Two infrastructural attributes in the form of spatial factors (lane width and lane type), and two attributes in the context of traffic conditions (speed difference and crowding on cycling tracks) are selected. The multi-level attributes and its values are displayed in the columns of Table 3.2.

Lane type	Lane width	Traffic volume	Speed difference
one-way	1.70 m	Peak hour	(+) 5 km/h
two-way	2.20 m	Off-peak hour	(+) 10 km/h

Table 3.2: Multi-level attribute values

Lane types

With respect to lane typology, *one-way* denotes cycling facilities that permit bicycle traffic in a single direction only, whereas *two-way* facilities accommodate bidirectional bicycle movements. As noted by CROW (2016a), the required lane widths for these configurations (i.e., one-way and two-way cycle tracks) differ even under comparable traffic volumes. The literature review further indicates that cyclists perceive encounters with oncoming users (i.e., meeting) as less safe than passing users traveling in the same direction (i.e., overtaking). This perception is particularly relevant on two-way cycle tracks, where cyclists are exposed simultaneously to opposing flows and same-direction overtaking maneuvers. Consequently, the lane type attribute is represented using two distinct levels: one-way and two-way cycle tracks.

Lane widths

For lane width, the literature yields that cycle lane widths could severely impact the level of safety. The lane width also interacts with the measured or expected number of cyclists during peak hours according to CROW (2016b). Generally, lane widths are adjusted according to the peak hour numbers to accommodate safe active transportation and to ensure sufficient space for overtaking. Hence, a similar amount of cyclists during a certain moment with different lane width yields different impacts on the feeling of safety. The lane width values are selected based on matching lane widths from the full list of locations. For each lane configuration, two different lane widths are chosen which remain equal across the lane types (e.g. a lane width of 2.20 meters remains unchanged for both 1-way and 2-way cycling tracks). The lane width measurements are subject to a measuring error of +/- 5 cm.

Speed heterogeneity

The speed difference attribute is subdivided into two levels of overtaking speeds. Discussion with safety experts, representatives of Gemeente Amsterdam, and the Fietsersbond led to various options in varying the speed differences. These options varied from varying the attribute with slight differences of + 2/3 km/h to extending the range to + 15 km/h. However, the actual cycling speeds within the scenarios must be constrained to legal speed boundaries (< 26 km/h). In addition, it would be infeasible to cycle at speeds that are considerably lower than the average cyclist speed (18 km/h) since other cyclists will pass at significantly higher speeds during the capturing of the videos. Moreover, to ensure that the various levels in speed heterogeneity are clearly visible in the videos, the difference between the attribute levels of speed heterogeneity must contain sufficient differentiation. Within this cycling speed boundaries, attribute levels of + 5 km/h, and +10 km/h during overtaking have been selected. The difference in attribute levels has been set on 5 km/h to ensure that the various levels in speed heterogeneity are clearly visible in the videos. Additionally, the overtaken cyclists must maintain a pace which is not considerably lower than the average cyclist speed (18 km/h) to ensure realistic representation with respect to other cyclists that are captured in the videos. The cycling speed values may contain an accuracy error of +/- 0.5 km/h.

Crowding

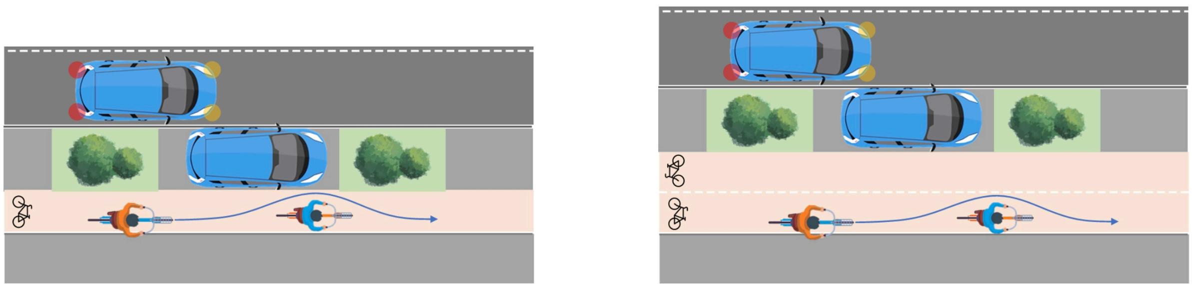
The attribute levels regarding crowding on cycling tracks are identified as *peak-hour* and *off-peak hour*. These levels refer to the number of nearby cyclists that could potentially impact the level of subjective safety. Possibilities in determining the attribute levels entailed counting the cyclist on that cycling track during each scenario or reproducing a scenario that feels either uncrowded (i.e. off-peak hour) or crowded (i.e. peak hour) by capturing moments where almost none or many cyclist are present respectively. In terms of methods, the latter was selected due to its pragmatic method of replicating the attribute levels. During peak-hour, a scenario is simulated wherein respondents perceive the feeling of cycling in a busy environment. On the contrary, off-peak hour display low levels of cyclists on that particular timestamp.

3.3. Location selection

A key challenge for this research was the selection of representative locations for filming. An initial iteration of location choosing was based on objective safety data (i.e. crash data of cyclist-to-cyclist, e-bike-cyclists, one-sided cyclist crashes). However, as Stülpnagel, Petinaud, and Lißner (2022), W.P. Vlakveld (2008), and SWOV (2012) indicate, there is no evidence based correlation between the level of objective safety and the level of subjective safety. Hence, it was decided not to continue with this method. Iteration 2 was grounded based on a so-called 'Online Hotline' from Fietsersbond (2020), where cyclists within Amsterdam could indicate locations and objects where they did feel unsafe cycling, similar to low levels of perceived safety. However, after discussions with two representatives from the Fietsersbond Amsterdam, it was concluded that the online hotline yielded an insufficient response rate to state any valid conclusions. Hence, the findings' validity from iteration two in searching for locations are rejected.

During both previous iterations and throughout discussions with Arcadis' safety experts, which occurred simultaneously, it became evident that one practice was consistently being considered, namely potential locations were all interlocutors indicated feeling unsafe during cycling and explained why. Thus, as a third iteration, locations were elected based on a multi-angle approach of the researcher's own perspective of subjectively unsafe locations and, on the other hand, the perspective of the safety experts, the researcher's direct network such as friends and family, experts from the Gemeente Amsterdam, and lastly representatives of Fietsersbond Amsterdam. This combination yields a variety of location that are not merely biased on experts' opinion but also on daily commuters without a specialization in safety in the context of active mobility.

Figure 3.3 provides a schematic representation of how a location should ideally look like during assessing and matching with the experiment's drafted scenarios. Both subfigures show a top-down view of one and two-way cycle tracks respectively and display the overtaking maneuver that will be performed during the experiments. In case of figure b, the overtaking occurs on the half of the cycling track in the direction of cycling to ensure that the lane width stays consistent with one-way lanes. It should be noted that realistically speaking, cyclists will also use the other half of the two-way lane during overtaking.

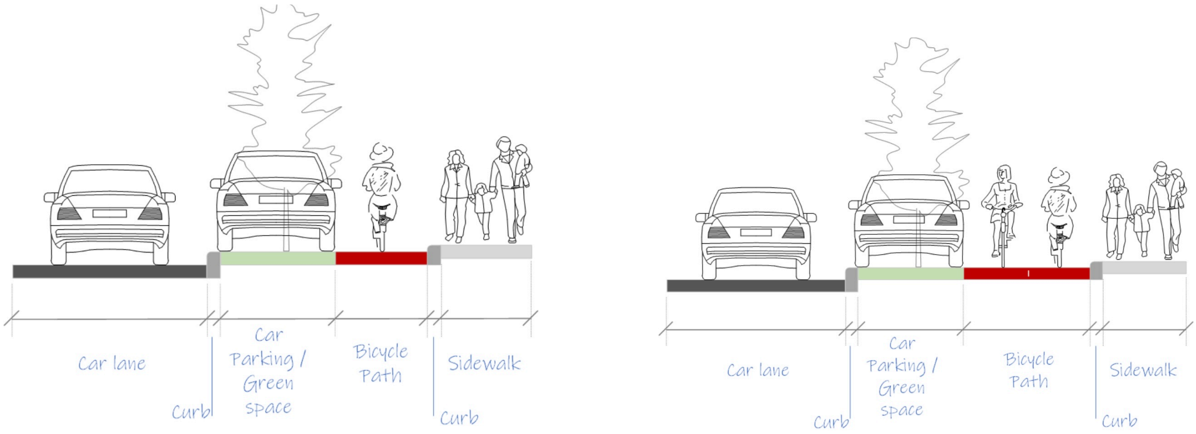


(a) One-way cycle track

(b) Two-way cycle track

Figure 3.3: Schematic top-down view of the locations

Figure 3.4 display a sideways view of both lane types. The cycle tracks are separated with objects in the form of parked cars, trees, and occasionally parked bicycles on the right side, and a sidewalk on the left side of the direction of cycling.



(a) Side view of a one-way cycle track

(b) Side view of a two-way cycle track

Figure 3.4: Schematic sideways view of the locations

Throughout the scouting for suitable locations, a master location inventory including locations within Amsterdam is build wherein the values for all one-level and two-level attributes are integrated. Each location within the mastersheet has been visited either virtually with Google street view or on-site. On-site visits guarantee the latest cycling lane developments regarding any road works. In addition, by having the ability to assess attribute in more detail, on-site visits lead to more accurate attribute values than visiting a location virtually. Lastly, Google street view might display an outdated visualization of locations (e.g., the virtual display of Geldersekade in 2023 with separate cycling and car lanes which has currently been transformed into a so-called 'cycling street'). Hence, locations selected for the final survey input are each separately visited on-site to assess whether it differs from its virtual Google street view equivalent. Table 3.3 shows the selected locations with the attribute values *lane type* and *lane width*, and its corresponding attribute values.

Location	Lane type	Lane width
Cruqiuskade	2-way	2.20 m
Wittenburgerstraat	2-way	1.75 m
Adm. De Ruyterweg	1-way	2.20 m
Marnixstraat	1-way	1.75 m

Table 3.3: Lane Types and Widths at selected locations

For each location in Table 3.3, attributes values from the factors such as lane width (measured in meters) and lane type (one-way or two-way) were identified and matched with the pre-selected attribute levels.

3.4. Filming setup

The capturing of video's that correspond to the attribute values of the attributes *lane type* and *lane width* that represent the experiment's scenarios is part of the core focus in this research. To ensure minimal variety among environmental factors (e.g., weather variables), all videos of the full factorial orthogonal design are captured in a period of similar weather circumstances, to satisfy the constraint of one-level attributes being tied to a fixed value. The filming of the various scenarios occurred at four locations in Amsterdam over a period of three weeks throughout the months of July and August. For each location, four distinct scenarios are being replicated from the perspective of the overtaken cyclist and the overtaking cyclist. Each location-tied scenario contains a different combination of the level of crowding on cycling lanes, and the level of speed difference between the two cyclists.

During filming, two Gopro Hero 11 cameras which were attached to a chest mount (i.e. Gopro Chesty) are used for capturing the footage from the two perspectives. In addition, two e-bikes are used with each distinctive devices to measure its own speed to facilitate accurate scenario representations in terms of speed differences.

It is crucial that errors were removed before full distribution to a large panel of respondents. Hence, the videos were validated on sight to check for any inconsistencies. In case the videos were identified as accurate and useful , they were be incorporated in the video-based survey.

Two GoPro Hero 11 cameras were used for capturing two perspectives of the overtaking event on the cycling track. The following configurations are used to obtain videos which are deemed optimal for these types of experiments.

- Videos of 20 - 25 seconds each to ensure sufficient remaining time (10 - 15 seconds) after video trimming.
- 1080 p | 30 frames per second | Superview to establish solid filming quality wherein the environment a sufficiently captured and to simulate the feeling of riding a bicycle.
- Autoboost on to minimize lens distortion which might arise while cycling.
- Zoom - [No]
- White balance - [Auto] to capture the realistic environment without manipulating the colors.
- Beeps - [on] To safely signalize the camera operator in case the start or stop button have been pushed during cycling.

After filming and a brief on-sight round of validation, the videos are trimmed to the target length of 10 to 15 seconds and labeled systematically to quickly identify which scenario these represent. Labeling happens in the form of configuring titles to a location of filming, including its attribute levels. Subsequently, the labeled videos are inserted into Final Cut Pro to blur faces and license plates that are captured in the videos. After processing, the videos are uploaded on Youtube with as setting 'not published' so that merely respondents of the survey can watch these. Lastly, the Youtube videos are embedded into Qualtrics so that it maintains it video quality when displayed to the respondents.

3.5. Questionnaire design

To accurately capture cyclists' perceptions of speed heterogeneity, a video-based questionnaire was chosen as the experimental method. Unlike static images or text-based descriptions, video footage allows respondents to experience the dynamic aspects of speed differences. The dynamic element is key for understanding how variations in cycling speed influence perceived safety. Additionally, video-based stated preference experiments enhance realism which enables participants to evaluate scenarios that capture realistic real-world conditions.

3.5.1. Survey items

The questionnaire commences with 7 questions centered around sociodemographic data such as age, gender, and geographical location. In addition, questions to gain insights into cycling frequency and what type of bicycle is used for own journeys. Lastly, since the core of the questionnaire contains visual stimuli, two questions regarding eye sight and color-blindness are integrated.

1	What is your age?	Option list
2	What is your gender?	Option list
3	Do you wear glasses or contact lenses?	Option list
4	Colour-blindness	Option list
5	What is your weekly cycling frequency?	Option list
6	Bicycle type usage on a weekly base	Option list
7	In what city or village do you live?	Open answer

Table 3.4: Part I - Sociodemographic questions

The second part of the questionnaire contains video-based questions where respondents must choose between two scenarios. After choosing, two 5-point Likert-scale rating questions about each scenario are asked to rate each video on a scale of safety. Respondents are faced with this combination of questions sixfold. This twofold approach leads to insights regarding a comparison of two scenarios and the rating of individual scenarios.

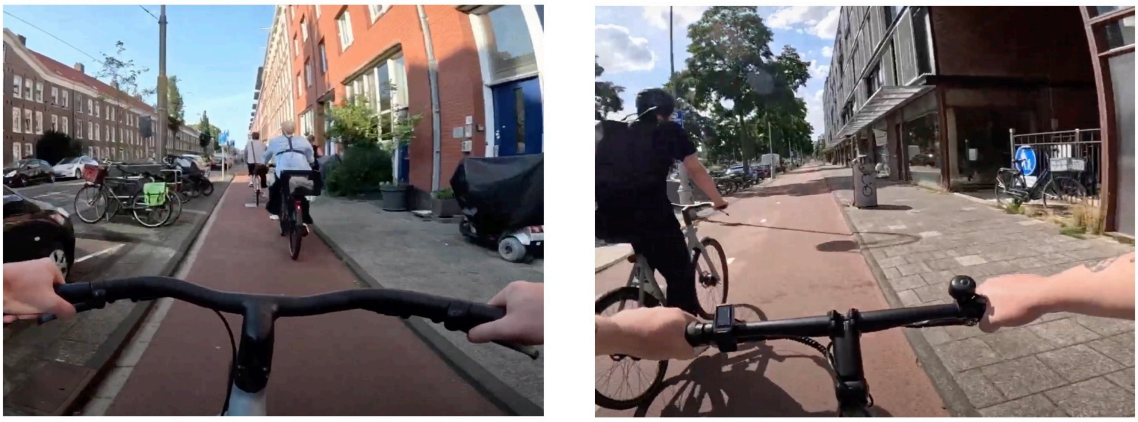


Figure 3.5: Part II - Example of scenario A and B

8	What is the safest scenario?	□	■
9	How safe do you feel in scenario A/B?	5-point scale	5-point scale

Table 3.5: Part II - Video-based questions

The last part of the survey displays two follow-up questions regarding statements examining the level of subjective safety in certain traffic situations. In this context, respondents must choose their level of safety on a 5-point scale from completely disagree [1] to completely agree [5]. A first statement regarding high speeds is presented to ask the respondents about their general opinion on high cycling speeds. In addition, a statement regarding Fatbikes is displayed to check whether respondents have a negative image regarding this bicycle type. To validate whether the binary attributes were effectively displayed in the videos, the questionnaire is closed with a multiple-choice question on what type of factors influenced the feeling of safety.

10	I feel unsafe when other cyclists drive at high speeds.
11	I feel unsafe when many cyclists on Fatbikes are driving nearby.
12	What factors did influence your feeling of safety?

Table 3.6: Follow-up questions on cycling safety

3.5.2. Full factorial design

To create a discrete choice experiment, a first step is the generation of full list of possible scenarios. Table 3.7 presents the full factorial design for each of the two cyclists' perspectives that were derived of the combinations of four multi-level attributes.

Scenario	Lane type	Lane width	Traffic volume	Speed difference
1	one-way	1.70m	Peak hour	(+) 5 km/h
2	one-way	1.70m	Peak hour	(+) 10 km/h
3	one-way	1.70m	Off-peak hour	(+) 5 km/h
4	one-way	1.70m	Off-peak hour	(+) 10 km/h
5	one-way	2.20m	Peak hour	(+) 5 km/h
6	one-way	2.20m	Peak hour	(+) 10 km/h
7	one-way	2.20m	Off-peak hour	(+) 5 km/h
8	one-way	2.20m	Off-peak hour	(+) 10 km/h
9	two-way	1.70m	Peak hour	(+) 5 km/h
10	two-way	1.70m	Peak hour	(+) 10 km/h
11	two-way	1.70m	Off-peak hour	(+) 5 km/h
12	two-way	1.70m	Off-peak hour	(+) 10 km/h
13	two-way	2.20m	Peak hour	(+) 5 km/h
14	two-way	2.20m	Peak hour	(+) 10 k/h
15	two-way	2.20m	Off-peak hour	(+) 5 km/h
16	two-way	2.20m	Off-peak hour	(+) 10 km/h

Table 3.7: Full factorial design scenarios

In the context of part II of the questionnaire (video-based questions), four binary attributes have been selected for the final design. To determine the number of alternatives within the full factorial design, all four attributes and the number of its attribute levels are inserted in formula (3.2). Since two perspectives are captured in each distinct scenario, the perspectives are transformed into an additional attribute and be treated as an attribute with two levels (the perspective of the cyclists who overtakes and the cyclist that gets overtaken). Thus, the number of attributes within each alternative is now 4 + 1 = 5. The number of attribute levels remains unchanged (2). The compute the number of unique alternatives within the full factorial design, the following formula is used:

$$\text{Number of alternatives} = L^N \tag{3.1}$$

Wherein L equals number of attribute levels (2), and N = the number of attributes within each alternative (5). This yields the following equation:

$$\text{Number of alternatives} = 2^5 = 32 \tag{3.2}$$

The number of unique combinations from each perspective (person who overtakes and the overtaken person) equals 16. Subsequently, using the computed number of unique alternatives, the total number of unique choice sets can be calculated using the binomial coefficient formula stated in (3.3).

$$C(n,r) = \binom{n}{r} = \frac{n!}{r!(n-r)!} \tag{3.3}$$

Inserting the number of alternatives that 3.2 yields as n and the number of choice tasks within each choice sets results into the following computation:

$$C(32,2) = \binom{32}{2} = \frac{32!}{2!(32-2)!} = 496 \tag{3.4}$$

With a survey design of 4(+1) attributes, varying in 2 attribute levels setup, and 2 alternatives within a choice set, a total of 496 unique choice sets can be generated to show the respondents. However, respondents cannot be faced with all choice sets due to cognitive overload, time restrictions within the survey and an increasing chance on more errors as a results of fatigue. Hence, a subset is selected wherein statistical information is maximized and trade-offs between the variables can be recognized. The design should minimize the variance of the estimated parameters to ensure that standard errors stay as small as possible.

3.5.3. D-efficient design

To satisfy the prerequisites stated in the previous subsection, a decision must be made regarding which choice sets must be showed to respondents and in what order. Subsequently, a D-efficient experimental design was adopted to construct the choice sets because it provides a statistically optimal way to estimate model parameters while keeping the number of scenarios manageable for respondents (maximum of 6 choice sets per respondent). Unlike a traditional orthogonal design, which focuses solely on eliminating correlations between attribute levels, a D-efficient design minimizes the determinant of the variance–covariance matrix of the estimates, yielding more precise estimations with fewer choice tasks Molin (2023b). This is particularly important in this study, given the high number of potential combinations resulting from multiple attributes and levels. An orthogonal design would have required far more scenarios to maintain level balance and independence, creating impractically large choice sets and increasing respondent fatigue, which could in turn alter data quality. In contrast, the D-efficient approach allows for the construction of a reduced yet highly informative set of scenarios that maximizes statistical efficiency while respecting cognitive limitations.

However, since efficient designs use priors, there is always a risk on a wrong estimation of prior values due to bias or wrong interpretation. Wrong priors alter the efficiency negatively. Furthermore, according to Molin (2023b), more effort is required to obtain a correct efficient design due to an increase in decisions for modeling and obtaining suitable priors.

Thus, provided that the estimations of the priors are roughly accurate, the before-mentioned advantages make D-efficient designs ideally suitable for video-based stated preference experiments, where each scenario demands greater time and attention from participants.

3.6. Ngene setup

To generate the experimental design, the software programme 'Ngene' is used to construct a D-efficient design for a binary choice experiment. Ngene optimizes the minimum number required of participant for reliable results by balancing the number of pairwise comparisons and the number of respondents to achieve adequate statistical power Cranenburgh and Collins (2019).

3.6.1. Prior values

Ngene's D-efficient designs use priors, in this case approximations of priors are compelled based on reviewed literature regarding parameters to improve statistical efficiency, Cranenburgh and Collins (2019), which yields more accurate estimates. Priors are generated to ensure optimization of the Ngene software and to enhance accuracy in the survey design. The priors for this d-efficient design consist out of a '-' or '+' sign that determines the direction of the prior and a small prior value, also called directional priors. Molin (2023b) states that directional priors are still deemed as efficient for a d-efficient design while not consuming much research-related resources. In addition, compared to zero-priors, the efficiency of priors within the range of 0.1 - 0.3 improves efficiency of the design without the risk on capturing false patterns. Hence, priors between this range have been chosen based on discussions during focus groups. The constructed directional priors were validated by safety experts of Arcadis. The magnitudes and direction of each prior is displayed in table 3.8.

Attribute	Level (compared to ref)	Expected Effect	Prior (Beta)
Lane type	1-way	Safer (ref)	0
	2-way	Less safe	-0.2
Lane width	170 cm	Less safe (ref)	0
	220 cm	Safer	(+) 0.25
Crowding	Off-peak hour	Safer (ref)	0
	Peak hour	Less safe	-0.5
Speed heterogeneity	(+) 5 km/h	Safer (ref)	0
	(+) 10 km/h	Less safe	-0.25

Table 3.8: Prior values of each attribute that are inserted into Ngene

Table 3.8 contains the priors of all binary attributes that are being displayed in the video-based part of the questionnaire. For each attribute, the 0-value equals the reference level. The non-zero attribute value contains a prior value that is has either a negative or positive influence on the attribute compared to the reference attribute value. In terms of lane type, two-way lanes are expected to feel slightly less safe (– 0.2) compared to one-way lanes due to cyclists traveling the opposite direction. Wider lanes (220 cm) are assumed to improve safety perceptions (+ 0.25) compared to narrower lanes (170 cm), as they provide more space for overtaking. Riding during off-peak hours is treated as the safer reference, while peak-hour conditions reduce perceived safety (– 0.5) because of increased traffic. Finally, speed heterogeneity, where an increase in speed differences between cyclists' reduces the feeling of safety. Hence a +5 km/h variation is the safe reference, while a +10 km/h variation decreases perceived safety (– 0.25) because larger speed differences can cause discomfort and risk of conflicts.

3.6.2. Ngene syntax

Based on the estimated priors and the design type, a syntax containing the utility function of both alternatives in the choice set is created and inserted into Ngene. Here, persp, type, width, crowding, and speeddiff are the experimental attributes, all as binary variables taking values 0 or 1. The coefficients represent taste parameters, with prior values, presented within the brackets [], provided to improve the efficiency of the design. For instance, prior means of −0.20, −0.20, 0.25, and −0.50 were used for the coefficients of type, width, and crowding respectively, while priors of zero were assigned to coefficients where no prior information was available. In this experiment, both scenarios contain generic attributes.

Interaction effects were also specified to capture whether the effect of speed differences (i.e. speeddiff) depends on width or crowding. By incorporating these priors and interaction terms, the design is expected to yield more precise parameter estimates than an orthogonal design of equal size.

Table 3.9 presents the output of Ngene's d-efficient design containing all prior values and its corresponding p estimates and p t-ratios. The p estimates indicate the required number of respondents to obtain statistical significance at a 95 percent confidence interval. In this table parameter b6 contains the highest p estimate value (78.361), which requires a minimum number of 79 respondents before statistical significance is reached. Since the design is subdivided into 6 blocks, the p estimates must also be multiplied sixfold, yielding a final p estimate of 471 respondents for b6. Hence, at least 471 respondents are needed for this design to obtain statistical significance.

Prior	b1	b2	b3	b4	b5	b6	b7	b8
Fixed prior value	0	-0.2	0.25	-0.5	-0.25	0.175	-0.175	0
p estimates	Undefined	12.044	19.227	4.955	32.965	78.361	73.451	Undefined
p t-ratios	0	0.565	0.447	0.881	0.341	0.221	0.229	0

Table 3.9: Prior Values, Estimates, and T-ratios for N=1

Table 3.10 presents the d-error of the d-efficient design. The D-error is a measure of the overall accuracy of the parameter estimates. A lower D-error means a more efficient design.

Iterations:	8554
D error	0.306
A error	0.433
B estimate	92.754
S estimate	78.361

Table 3.10: D-error and number of iterations

By examining the table of choice probabilities, wherein the utilities and choice probabilities of each choice sets are computed, the dominance of the alternatives can be derived. In this context, a value of expected probability near 1 indicates a dominant alternative and yields limited trade-off information. Hence, these probability values should ideally be avoided. According to Molin (2023b), a rule of thumb is that the choice probabilities should be less than the value 0.90. The Ngene syntax indicated that no choice probability has a value of 0.90 or more.

3.7. Data collection

The questionnaire was distributed through a Dutch panel of respondents named Panel Inzicht. An paid agreement was made between Arcadis and Panel Inzicht to obtain a total of 600 Dutch respondents that will take part in answering the questionnaire. A prerequisite was that each respondent must be and adult and should be registered in one of the 41 largest municipalities within the Netherlands (G40). The questionnaire was distributed throughout two weeks in September 2025. After the panel quota of 600 responses was reached, an additional 25 respondents were acquired through the researcher's own network totaling a total amount of 625 responses. After closing the survey for distribution, invalid responses were filtered out. Therefore, a total amount of 609 responses were used as input for the using mixed logit model.

3.8. Data analysis

The responses of the questionnaire can be examined in several ways. This section includes the different methods regarding the analysis of the results. It explains the method behind mixed logit modeling and the scenario ranking and circumstantiates the choices made in this process.

3.8.1. Logit modeling

The choice data in this research is collected through the choice sets that were integrated in the questionnaire. The choice data contains the revealed preference (RP) of respondents in the domain of subjective safety. Examining this stated choice data allows for predictions regarding trade-offs between the variables involved. To understand how the respondents of the questionnaire make choices a discrete choice model (DCM) can be used. The choice model is grounded on the Random Utility Maximization (RUM) theory and can be stated by the following equation:

$$U_{ij} = V_{ij} + \varepsilon_{ij} \tag{3.5}$$

Formula 3.5 assumes that decision makers maximize the utility of their decisions which is the core of a discrete choice model.

A discrete choice model has several variations, among them the standard multinomial logit (MNL) and the Mixed Logit model (or Random Parameters Logit). Mixed logit is advantageous over the MNL because it overcomes the two major limitations of MNL. These two limitations concern the independence of irrelevant alternatives (IIA) assumption and the inability to capture preference heterogeneity. In this research, where respondents must evaluate cycling tracks which vary in attributes such as lane type, width, crowding, and speed differences, it is unrealistic to assume that all respondents have identical preferences or that unobserved factors across alternatives are uncorrelated. Mixed logit ensures that the coefficients of key attributes vary randomly across individuals, resulting in a more realistic representation of cyclist preferences and capturing unobserved taste differences that influence perceived safety. This produces results that better reflect the diversity of cyclists, making it the appropriate model for analyzing safety perceptions that are influenced by multiple attributes, as reported by Cranenburgh S. (2023a).

Since respondents are faced with multiple decisions throughout the survey, the decision of each choice set is influenced by their previous decisions, introducing correlation among their answers. Mixed logit can account for this panel structure by slightly modifying the likelihood function. In addition to the panel-based mixed logit model, latent class cluster analysis is also considered as an optional method to model these decisions.

Mixed logit offers several important advantages over latent class cluster analysis (LCCA) for this research. While latent class models force respondents into a small number of discrete groups with homogeneous preferences within each class, mixed logit models allow continuously distributed preference heterogeneity, which results in more accurate estimates. Moreover, attributes such as lane type, crowding, lane width, and speed differences are not suitable to serve as basis for creating cluster, e.g., a cluster of respondents who dislike crowding does not lead to effective insights for policy makers. Furthermore, according to Faber (2023), Mixed Logit avoids the need to pre-specify the number of latent classes, and therefore making additional assumptions which may lead to biased results.

Utility function

The utility function states that the attractiveness (utility) of an alternative (i) for individual (n) in choice situation (t) is determined by two components: the observed attributes of the alternative (e.g. lane width, crowding, or speed differences), and an unobserved error term. The observed part is calculated by multiplying the alternative's attributes by the individual's taste parameters. Here each variable contributes positively or negatively to utility depending on how much the person cares about it, while the error term accounts for factors that cannot be measured.

$$U_{nit} = \beta_n^{\top}\mathbf{x}_{nit} + \varepsilon_{nit} \tag{3.6}$$

where:

- U_{nit} is the utility individual n obtains from alternative i in choice task t,
- $\mathbf{x}_{nit}$ is the vector of observed attributes,
- β_n is the individual-specific taste vector,
- ε_{nit} is an i.i.d. extreme-value error term.

Conditional choice probability

The conditional probability gives the probability that an individual chooses alternative (i) in a specific choice situation, assuming we know their personal taste parameters. This formula compares the utility of alternative (i) with the utilities of all other alternatives in that choice set. Alternatives with higher utility are more likely to be chosen.

$$P_{nit|\beta_n} = \frac{\exp\left(\beta_n^\top \mathbf{x}_{nit}\right)}{\sum_{j\in C_{nt}} \exp\left(\beta_n^\top \mathbf{x}_{njt}\right)} \tag{3.7}$$

Panel Likelihood

The panel likelihood combines all of an individual's choices across multiple choice tasks. Because the survey presents several scenarios to each respondent, the model must explain a sequence of choices. The same taste parameters apply to all tasks for that individual, meaning the model assumes consistent preferences across time. By multiplying the probabilities for each choice situation, a likelihood is obtained regarding the entire pattern of choices of a respondent.

$$P_n(\beta_n) = \prod_{t=1}^{T_n} P_{ni_t t|\beta_n} \tag{3.8}$$

where T_n is the number of choice tasks completed by individual n.

Unconditional (mixed) probability

The final probability represents the core of the mixed logit model. Since an individual's true preferences is unknown, the model averages over all possible values, weighted by how likely each one is according to the assumed distribution. This creates a mixture of logit models. Because the integral cannot be solved analytically, it is approximated through simulation using many draws. This final mixed probability is what is used for estimating the model and predicting behavior.

$$P_n = \int \left[\prod_{t=1}^{T_n} \frac{\exp\left(\beta_n^\top \mathbf{x}_{ni_t t}\right)}{\sum_{j\in C_{nt}} \exp\left(\beta_n^\top \mathbf{x}_{njt}\right)}\right] f(\beta_n \mid \theta)\, d\beta_n \tag{3.9}$$

where $f(\beta_n \mid \theta)$ is the density of the random coefficients parameterized by θ.

3.8.2. Mixed Logit modeling decisions

Throughout the search for the most optimal model, several key decisions must be made to ensure the model accurately captures real-world heterogeneity while remaining statistically valid. The first set of decisions concerns which parameters should be random, what distributions they should follow, and whether correlation should be allowed among them. These choices determine how individual differences in preferences are represented in the model. Random parameters allow sensitivities to vary across people, making the model far more flexible than a standard multinomial logit.

Coding of the variables

To construct the mixed logit model Biogeme 3.3.1 Bierlaire (2023) was used. In this model, each non-constant attribute is included as a variable. Since all non-constant attributes in the scenarios are binary, dummy coding has been applied. The attribute levels and its corresponding dummy values are displayed in Table 3.11.

Table 3.11: Biogeme dummy values

Attribute	0	1
Perspective	Gets overtaken	Overtakes
Lane type	One-way	Two-way
Lane width	170 cm	220 cm
Crowding	Off-peak	Peak
Speed difference	(+) 5 kmh	(+) 10 kmh

In addition to the random variables, several sociodemographic variables were included in Biogeme 3.3.1 for the specification of the optimal mixed logit model. Apart from gender, the remaining sociodemographic variables (age group and cycling frequency) assume more than two distinct categories. Consequently, one-hot encoding was applied to conform to the data preprocessing requirements of Biogeme for mixed logit model estimation. In one-hot encoding, respondents belonging to a given sociodemographic subcategory (e.g. age group 18–24 years) are assigned a value of 1 if they fall within that subcategory, and 0 otherwise.

Distributions of the random variables

By implementing random coefficients in the Mixed Logit model, individuals will vary in their preferences regarding different attributes. For example, some respondents may be more sensitive to crowding than others. The formula presented below computes the Bèta value of each attribute based on the distribution of its random variable.

$$\beta_{nk} = \begin{cases} \mu_k + \sigma_k \eta_{nk}, & \text{if the coefficient is normally distributed,} \\ -\exp(\mu_k + \sigma_k \eta_{nk}), & \text{if the coefficient follows a lognormal distribution and is constrained to be negative.} \end{cases}$$

In the model, each random coefficient is defined through a mean and a standard deviation. Here, the parameter μ_k determines the average effect of attribute k, and σ_k determines how much individuals deviate from this average. Together, they produce a distribution of coefficients β_{nk} across the population.

Based on a combination of the prior values of each attribute and the feedback collected during the draft phase of the questionnaire from both safety experts and non-experts, the general direction of the impact of each attribute was established; for example, larger speed differentials were found to adversely affect perceived safety. Drawing on this initial set of responses, the random variables were specified using either a normal or a lognormal distribution. A normal distribution was assigned to those variables for which the attribute level of 1 does not necessarily induce a negative effect (e.g., wider lanes), whereas a lognormal distribution was used for variables where the attribute level of 1 is associated with a negative impact on perceived safety (e.g., peak conditions). The specification of each random variable as implemented in Biogeme 3.3.1 is presented below:

$$\beta^{(r)}_{\text{PERS}} = -\exp\Big(\mu_{\text{PERS}} + \sigma_{\text{PERS}}\, e^{(r)}_{\text{PERS}}\Big), \tag{3.10}$$

$$\beta^{(r)}_{\text{TYPE}} = -\exp\Big(\mu_{\text{TYPE}} + \sigma_{\text{TYPE}}\, e^{(r)}_{\text{TYPE}}\Big), \tag{3.11}$$

$$\beta^{(r)}_{\text{WIDTH}} = \mu_{\text{WIDTH}} + \sigma_{\text{WIDTH}}\, e^{(r)}_{\text{WIDTH}}, \tag{3.12}$$

$$\beta^{(r)}_{\text{CROWD}} = -\exp\Big(\mu_{\text{CROWD}} + \sigma_{\text{CROWD}}\, e^{(r)}_{\text{CROWD}}\Big), \tag{3.13}$$

$$\beta^{(r)}_{\text{SPEED}} = -\exp\Big(\mu_{\text{SPEED}} + \sigma_{\text{SPEED}}\, e^{(r)}_{\text{SPEED}}\Big). \tag{3.14}$$

In the context of the lognormal distribution formulas, these formulations make direct interpretation more difficult because the estimated μ and σ are not the actual mean and standard deviation of the random parameter. The true coefficient distribution is nonlinear and skewed, so the behavioural mean must be computed by transforming the parameters. Despite this extra complexity, the lognormal distribution is preferred for these variables because it guarantees that the effect always has the correct sign that is consistent with the outcomes of the draft questionnaire.

Model specifications

In addition, the number and type of draws must be chosen for simulation of the random terms. To test a variety of models, a small number of draws is used (100 - 500) to briefly check whether the adjustments are justified and potentially improve model fit. For the final models, such as the baseline model and the final model, the number of draws was increased to 1500 - 3000.

All possible interactions between the five attributes were formulated and checked for statistical significance on a confidence interval of 95% ($p < 0.05$). In addition, every possibility in the interactions between the attributes and the sociodemographic variables was examined. Statistical insignificant interactions were removed and a final model including all five random variables and its additional statistical significant interactions was estimated. As individuals make repeated choices, a panel specification is necessary to correctly capture within-person correlation over time.

The model presents model performance specifications such the log-likelihood (LL) and the Bayesian Information Criterion (BIC). These values indicate whether a model better fits the data compared to other model specifications. A model with a higher log-likelihood and a lower Bayesian Information Criterion (BIC) is preferred. A specification that improves LL and reduces BIC relative to alternatives is selected for further refinement. Finally, each model was checked on convergence. If the model did not converge, the results were considered as invalid. Conclusively, these decisions allow the Mixed Logit model to represent realistic choice behavior while remaining stable, interpretable, and well-identified.

Utility specification

The two expressions stated below define the systematic utilities of the two cycling alternatives (0 and 1) in the panel-based mixed logit model for respondent n in choice situation t under simulation draw r. Each utility is composed of the alternative-specific constant (only for alternative 1) and a weighted sum of the scenario attributes: perspective, lane type, lane width, crowding, and speed difference. Inserting the five attributes into the utility function of the mixed logit yields the following utility formulas:

$$V_{0nt}^{(r)} = \beta_{\text{PERS}}^{(r)}\,\text{PERS}_{0nt} + \beta_{\text{TYPE}}^{(r)}\,\text{TYPE}_{0nt} + \beta_{\text{WIDTH}}^{(r)}\,\text{WIDTH}_{0nt} \tag{3.15}$$

$$+ \beta_{\text{CROWD}}^{(r)}\,\text{CROWD}_{0nt} + \beta_{\text{SPEED}}^{(r)}\,\text{SPEED}_{0nt}. \tag{3.16}$$

$$V_{1nt}^{(r)} = \text{ASC}_1 + \beta_{\text{PERS}}^{(r)}\,\text{PERS}_{1nt} + \beta_{\text{TYPE}}^{(r)}\,\text{TYPE}_{1nt} \tag{3.17}$$

$$+ \beta_{\text{WIDTH}}^{(r)}\,\text{WIDTH}_{1nt} + \beta_{\text{CROWD}}^{(r)}\,\text{CROWD}_{1nt} + \beta_{\text{SPEED}}^{(r)}\,\text{SPEED}_{1nt} \tag{3.18}$$

$$+ \Delta_n. \tag{3.19}$$

$$\tag{3.20}$$

The above utility functions are utilized to compare the different scenarios. Each scenario contains different attribute values that will be inserted into the utility functions, and based on their total utility sum, the final utility is computed.

3.8.3. Scenario ranking

Besides analyzing the results with the panel-based mixed logit model, an additional method has been selected. While the mixed logit model yields values regarding pairwise-based comparisons, the ranking method evaluates the perceived safety of the scenarios as individual environments. Viewing the questionnaire's results from a different perspective yields an alignment between scenarios comparisons and individual scenario ratings. Hence, the scenario-based rankings can act as both a comparison and a validity tool for the mixed logit results.

This ranking method entails the ordering of all 32 scenarios (16 distinct scenarios from two different perspectives) that were displayed to respondents. Each distinct scenario in the questionnaire's choice sets was ranked by the question 'How safe would you rate scenario A/B?'. Responses were mandatory based on a 5-point scale ranging from [very unsafe] to [very safe].

To compute the arithmetic mean value and apply a statistical test for mathematical validity, textual responses have been altered to numerical values ranging from 0 [very unsafe] - 2 [neutral] - 4 [very safe]. The scenarios were ordered based on the arithmetic mean of each scenario ranging from scenarios perceived as most safe (high mean) to scenarios that were perceived as less safe (lower mean).

Finally, the Friedman test was applied as statistical test to validate whether the mean-based ranking is statistically meaningful. The formula of the Friedman test is stated in 3.21.

$$\chi_F^2 = \frac{12}{nk(k+1)} \sum_{j=1}^{k} R_j^2 - 3n(k+1) \tag{3.21}$$

where:

- χ_F^2 ; is the Friedman test statistic.
- n ; is the number of subjects (or respondents), i.e., the number of repeated measurements.
- k ; is the number of conditions or treatments being compared (in this case, the number of scenarios).
- R_j ; is the sum of ranks for condition j across all subjects.
- $\sum_{j=1}^{k} R_j^2$; is the sum of the squared rank totals for all k conditions.

The Friedman test was applied to examine whether there were statistically significant differences in respondents' evaluations across the 32 scenarios. The test revealed a significant overall effect of scenario on ratings, $\chi^2(31) = 330.12$, $p < 0.001$.

3.8.4. Computing scenario choice probabilities

To check whether respondents differ in their reaction towards a forced choice questions, which serves as input of the mixed logit model, and a rating question, acting as input for the scenario ranking, the attribute values of each scenario have been inserted into the utility function. The utility function comprises of the Bèta values that were computed based on the μ and σ of the main attributes. Since not every scenario entails statistically significant interactions, interaction are excluded from the utility function.

Since scenario 1018 serves as the median value based on ranking of the computed utilities per scenarios, it was selected as the baseline scenario. The five highest and lowest ranked scenarios in the mean-based scenario ranking are compared with this baseline scenario, resulting in the choice probabilities when these scenarios are compared with the baseline scenario within a choice set. Scenario 1018 exhibits a video from the overtaker's perspective, on a one-directional, narrow (1.7m) cycling track, with an overtaking speed of + 10 kmh difference during off-peak hours. The choice probabilities for each scenario are computed using the standard binary logit formula:

$$P(a) = \frac{e^{U_a}}{e^{U_a} + e^{U_b}}$$

where U_a is the utility of alternative a, and U_b is the utility of the baseline alternative b. The term e^{U_b} identifies the baseline scenario (1018), which has a utility value of -0.62. Applying this formula to the five highest and lowest mean-based rated scenarios allows for a comparison on choice probabilities between these scenarios.

4

Analysis and Results

This chapter presents the results of the questionnaire's outcomes. Section 4.1 presents a descriptive analysis of the survey's sample. Additionally, it provides and compares the reaction of various subgroups on two statements that were displayed in the questionnaire. Section 4.2 presents the results of the mixed logit model. Section 4.3 states the results of the scenario ranking method. This chapter ends with section 4.4, which describes the outcomes of the scenarios ranking values that served as input for the mixed logit utility function. In addition, the choice probabilities for the highest and lowest rated scenarios are visualized in this section.

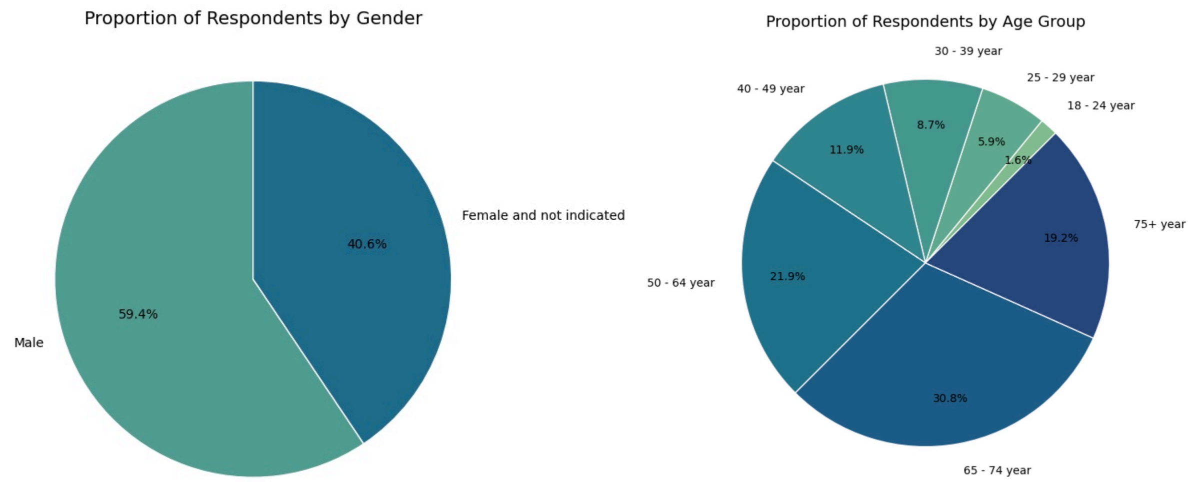
4.1. Descriptive analysis

To describe the population sample of survey's respondents, pie charts visualizing the proportions of gender, age groups, the levels of weekly cycling frequency, and the weekly used bicycle types, have been constructed. Presenting the proportions of these sociodemographic characteristics makes it possible to understand who participated in the study and to what extent the sample represents the broader cycling population. This overview is important for interpreting the preferences regarding statements entailing high speeds and Fatbikes, as sociodemographic factors can influence perceptions of cycling infrastructure. Additionally, reporting these characteristics increases transparency in the sample and allows possible identifications of sampling biases. Lastly, subgroups could be created for the sake of comparison in the context of the survey's statements section.

4.1.1. Characteristics of the sample

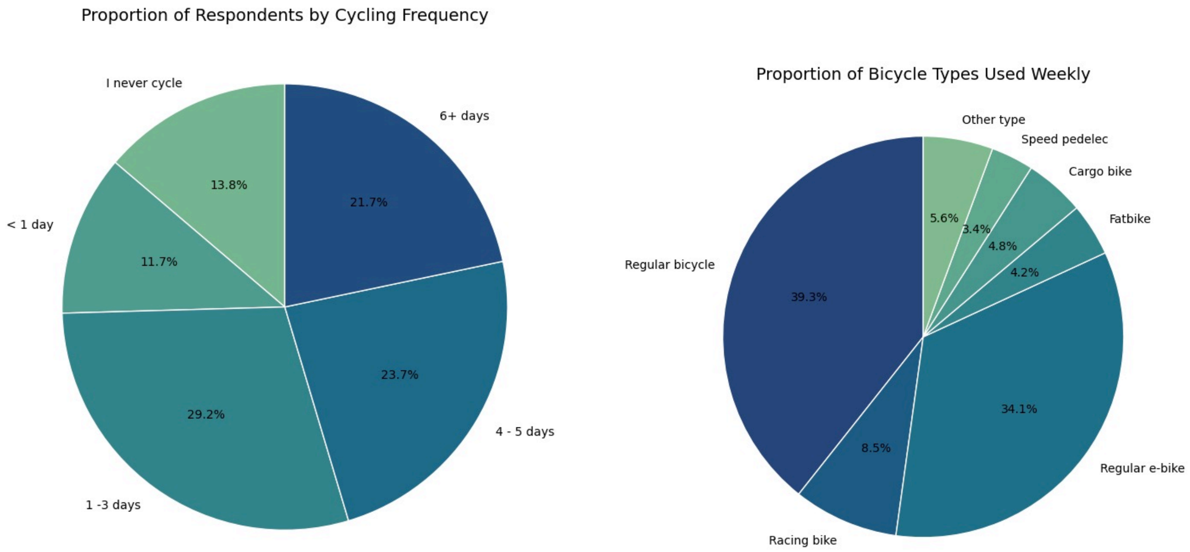
The characteristics of all respondents are showed in in various pie charts in figures 4.1 and figure 4.2. The proportion among gender is equally divided whereas the distribution of the different age groups indicates that the sample has a large percentage of respondents from older generations.

Regarding weekly cycling frequency, it can be noticed that 13.8% of the respondents indicates that they never cycle on a weekly base. On the contrary, 21.7% specified that they were cycling 6 or more days on a weekly base. Hence, this is the group of regular cyclists. In addition, considering the weekly used bicycle types, an amount of 39.3 % indicated to ride a regular bicycle at least once per week. Similarly, a proportion of 34.1% of the sample rides a regular e-bike at least once in a similar timeframe. Less chosen bicycle categories such as a cargo bike, speed pedelec, which has a maximum speed of 45 km/h, a racing bike, and a Fatbike, which identifies as a subcategory within the e-bike sector, all have a relative low percentage (< 10%) when it comes to weekly use. It should be noted that respondents were given the ability to select multiple bicycle types as for their weekly ride if that was the case.



(a) Gender distribution (b) Age group distribution

Figure 4.1: Overview of sample characteristics



(a) Weekly cycling frequency distribution (b) Weekly used bicycle types

Figure 4.2: Overview of cycling behavior among respondents

Table 4.1 presents the characteristics of the questionnaire's respondents. The sample consist out of 630 respondents where 620 respondents submitted a valid response. The respondents were faced with 6 choice sets, totaling an amount of 3720 choice tasks. The table also presents the sociodemographic details of the population of the Netherlands in 2024, which is extracted from the CBS (2023) age pyramid. This figure was selected due to its inclusions of non-cyclists, a group that is also represented in the sample of this research.

Table 4.1: Comparison of sample versus national demographics

Variables	Categories	Sample N	%	CBS (> 18 years)	%
	Total	620	100.0%	14638000	100%
Age group	18 – 24 years	10	1.6%	1613000	11.0%
	25 – 29 years	27	4.4%	1172000	8.0%
	30 – 39 years	55	8.9%	2344000	16.0%
	40 – 49 years	75	12.1%	2126000	14.5%
	50 – 64 years	138	22.3%	3710000	25.3%
	65 – 74 years	194	31.3%	1968000	13.4%
	75 years or older	121	19.5%	1705000	11.6%
Gender	Male	363	58.5%	7227000	49.4%
	Female	247	39.8%	7411000	50.6%
	Other / not indicated	10	1.6%	-	-
Cycling frequency	Never	85	13.7%	-	-
	< 1 day/week	72	11.6%	-	-
	1–3 days/week	180	29.0%	-	-
	4–5 days/week	146	23.5%	-	-
	6+ days/week	134	21.6%	-	-
	Not indicated	3	0.5%	-	-
Contact lenses or glasses	Yes	412	66.5%	-	-
	No	207	33.4%	-	-
Colour blindness	No	579	93.4%	-	-
	Yes	31	5.0%	-	-
	I don't know	3	0.5%	-	-

When comparing the sample with the national population of the Netherlands some differences can be observed. Most notably, the sample contains an over-representation of older respondents, particularly within the age groups 65 – 74 years and 75 years or older. In contrast, younger age groups (between 18–24 years and 25 – 29 years) are underrepresented. Additionally, the gender distribution in the sample is reasonably aligned with national data, though males are slightly overrepresented. The cycling frequency distribution cannot be compared to CBS data due to the absence of equivalent national frequency data. Overall, while the sample is sufficiently diverse for mixed logit modeling, the outcomes lean mostly on older cyclists.

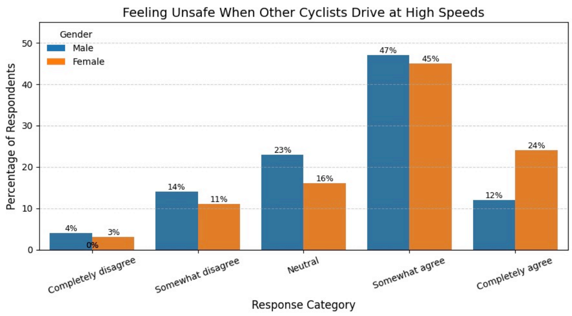
4.1.2. Distribution of statement responses

In addition to the overall sample characteristics, subgroups were constructed to enable comparison of responses to two survey statements across groups differing in their sociodemographic attributes. These subgroups were compared with respect to their responses to two items included in the questionnaire. The first item assessed the extent to which respondents feel unsafe when other cyclists ride in close proximity at high speeds. The second item examined whether respondents would feel unsafe when a large number of Fatbikes are cycling nearby. For both statements, respondents indicated their level of agreement on a scale ranging from "completely disagree" to "completely agree." The corresponding results are presented in Figures 4.3, 4.4, and 4.5.

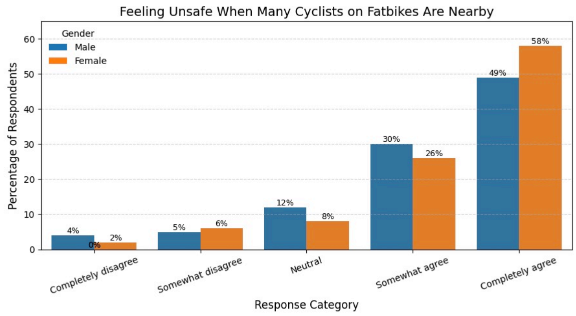
4.1.3. Gender-based comparison

In the context of the gender comparison, both males (N = 365) and females(N = 247) tend to roughly react similar to both statements. When observing the Speed statement outcomes more closely it can be observed that women tend hold a stronger opinion regarding feeling unsafe when many cyclists driving closely at high speed compared to men (24% versus 12% respectively). Overall, a majority of both men (59%) and women (69%) either somewhat or fully agree on feeling unsafe in case of many high-speed cyclists are driving nearby, whereas a portion of 18% for male and 14% for female (partially) disagree on this statement.

Considering the statement whether a respondent feels unsafe when many cyclists on Fatbikes cycle nearby, both males and female seem to have a stronger opinion compared to their response to the high-speed cyclists statement. The tendency of agreement with this statement is higher among both demographic groups. Similarly to previous statement, the female group tends to contain a stronger opinion compared to its male counterpart. Overall, the portion of females (partially) agreeing to this statement is significantly higher than the portion who either somewhat or completely disagrees (84% vs 8%). Likewise, the perceptual allocations of male (partially) agreeing is also substantially larger than the portion (partially) disagreeing (79% and respectively 9%).



(a) Responses of the gender subgroups to high speeds



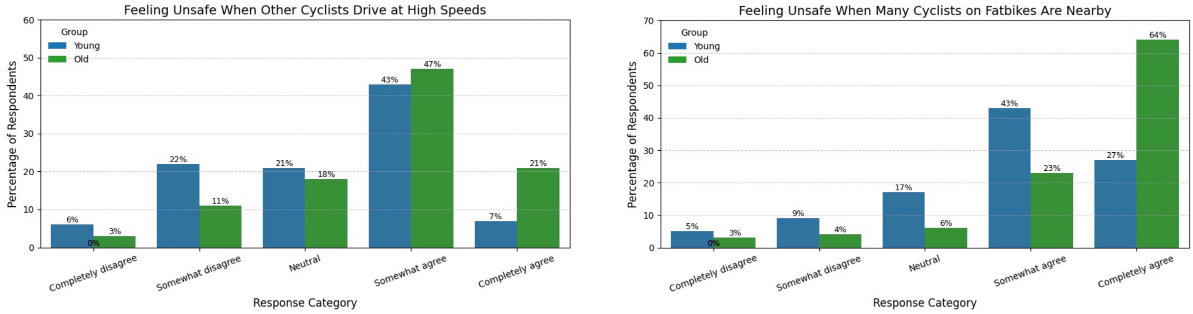
(b) Responses of the gender subgroups to nearby Fatbikes

Figure 4.3: Distribution of responses by gender-based subgroups

4.1.4. Age-based comparison

Regarding the age-based comparison between the age groups younger than 29 years (N = 39) and older than 65 years (N = 311), the results indicate differences between younger and older cyclists in how they perceive safety when cycling near others at high speeds. Among younger respondents, 50% (7% completely agree and 43% somewhat agree) feel unsafe in such situations, whereas this share increases to 68% among older respondents (21% completely agree and 47% somewhat agree). Additionally, younger cyclists are more likely to somewhat disagree (22%) compared to older cyclists (11%). These statistics can indicate that younger individuals are generally more accustomed to higher speeds or feel more confident in fast-moving environments. These patterns stipulate that perceived safety in high-speed cycling situations tend to vary with age.

When examining perceptions related to the presence of many Fatbikes, the differences between age groups become even more clear. Among younger cyclists, 70% agree to some extent that this situation feels unsafe, while this proportion increases to 87% for older cyclists. Notably, 64% of older respondents completely agree with the statement, indicating a strong emotional response concerning Fatbike-related conditions. Although younger respondents also show concern, their responses are more moderate, with a greater share selecting somewhat agree rather than completely agree. This implies that while Fatbikes are perceived as a safety concern across both sociodemographic groups, older cyclists have a stronger opinion regarding their feelings of safety.



(a) Responses of the age-based subgroups to high speeds

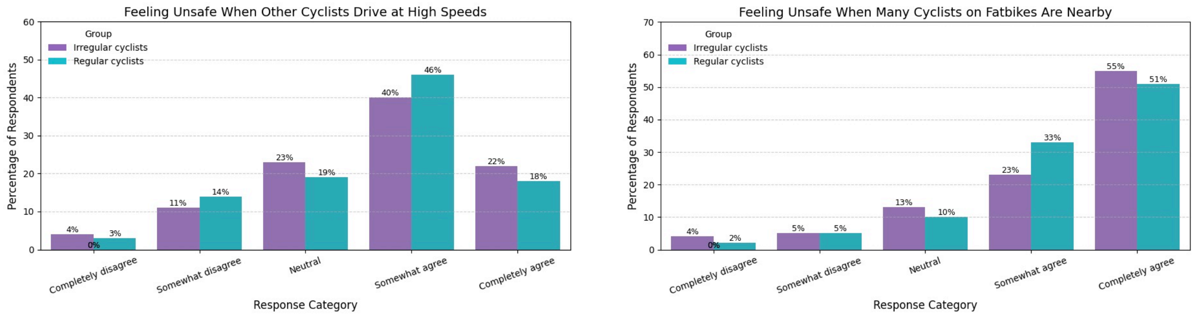
(b) Responses of the age-based subgroups to nearby Fatbikes

Figure 4.4: Distribution of responses by age-based subgroups

4.1.5. Cyclist type comparison

A third comparison has been made between regular cyclists (respondents who cycle more than 4 days on a weekly base, N = 168) and irregular cyclists, a group that contains respondents who never cycle (N = 86). The responses belonging to both groups yield roughly similar trends with subtle differences. Both groups largely agree that cycling at high speed contributes to feelings of unsafety, with 62% of irregular and 64% of regular cyclists indicating some level of agreement. However, irregular cyclists are more likely to completely agree (22% versus 18%), which may suggest a stronger immediate sense of discomfort. Regular cyclists, on the other hand, show a higher share of somewhat agree responses (46% versus 40%), which could imply a more measured assessment.

The perception of safety when many cyclists on Fatbikes are nearby shows stronger and more consistent feelings of unsafety across both groups. A majority of respondents agree or completely agree, 78% of irregular and 84% of regular cyclists, indicating that the presence of Fatbikes generates a sense of feeling unsafe. While both groups reveal concerns, irregular cyclists are slightly more likely to completely agree (55% versus 51%), and thus showing stronger emotional reactions to such conditions. Regular cyclists more often somewhat agree (33% versus 23%), reflecting a less intense but still significant feeling of unsafeness. Lastly, the smaller neutral and disagreement proportions stipulate how respondents with different cycling weekly cycling frequencies recognize the safety challenges posed by Fatbikes in a similar way.



(a) Responses of the cycling frequency-based subgroups to high speeds

(b) Responses of the cycling frequency-based subgroups to nearby Fatbikes

Figure 4.5: Distribution of responses by cycling frequency-based subgroups

4.2. Panel-based Mixed Logit

To analyze the results of the forced choice questions a mixed logit model was applied. Firstly a baseline model is estimated wherein all variables are transformed into random variables. This baseline model excludes any sociodemographic or interaction variables. In addition to the baseline mode, a second model is estimated wherein all statistically significant interaction are included.

4.2.1. Baseline Mixed Logit model

The baseline mixed logit model output presented in table 4.2) presents all five random variables without any interactions. The table reveals that perceived cycling safety is influenced by lane type, crowding, speed difference, and the perspective of filming (perspective of the overtaken versus the perspective of the person who overtakes). Each of these statistically significant variables has a negative coefficient, indicating that a filming perspective from the person who overtakes reduces perceived safety. Similarly, a two-way cycling track, an increase in crowding of cyclists, and a greater speed differences during an overtaking manoeuvre decrease the level of safety perception. On the contrary, the lane width variable is stated as statistically insignificant, indicating that differences in lane width do not have a meaningful impact on perceived safety in this sample. Still, while lane width alone is not significant, its effect may still depend on other conditions.

In terms of heterogeneity among individuals responses, respondents within the sample differ in how much lane width matters due to the significant sigma. Since significant heterogeneity for lane type, lane width, and speed differences is also demonstrated by the model's output, it suggests that individuals seem to react differently to varying levels of these attributes. Lastly, The alternative-specific constant ($\text{ASC}_1 = 0.119$) implies a small but systematic preference for the second alternative. This value possibly relates to the presentation order of the various scenarios within the survey design.

Table 4.2: Mixed Logit Baseline model of the five random variables

Variable	**Estimate**	**s.e.**	**t-ratio**	**p-value**
$\mu_{\text{PERSPECTIVE}}$	-1.63	0.259	-6.29	< 0.001
$\sigma_{\text{PERSPECTIVE}}$	-7.52	44.5	-0.169	0.866
$\mu_{\text{LANE\_TYPE}}$	-15.0	0.057	-266	< 0.001
$\sigma_{\text{LANE\_TYPE}}$	-2.17	0.005	-383	< 0.001
$\mu_{\text{LANE\_WIDTH}}$	0.008	0.048	0.161	0.872
$\sigma_{\text{LANE\_WIDTH}}$	-0.587	0.154	-3.81	< 0.001
μ_{CROWDING}	-1.19	0.238	-5.01	< 0.001
σ_{CROWDING}	0.183	0.199	0.921	0.357
$\mu_{\text{SPEED\_DIFFERENCE}}$	-1.07	0.122	-8.76	< 0.001
$\sigma_{\text{SPEED\_DIFFERENCE}}$	-9.64	1.44	-6.67	< 0.001
ASC_1	0.119	0.042	2.86	0.004
Model Fit Statistics				
Number of estimated parameters	11			
Sample size	607			
Observations	3665			
Final log likelihood	-2424.50			
Rho-square (ρ^2)	0.029			
Adjusted Rho-square ($\bar{\rho}^2$)	0.025			
Akaike Information Criterion (AIC)	4870.99			
Bayesian Information Criterion (BIC)	4919.48			

4.2.2. Final Mixed Logit model including interactions

The final mixed logit model presented in Figure 4.3 extends the baseline specification by including statistically significant interaction terms between the various binary-level attributes and several sociodemographic variables, e.g., age, gender, cycling experience.

The full interaction-based model in Table 4.3 reveals that the addition of interaction terms increases the model fit. The final log likelihood of the full model containing interaction terms (-1781.098) is significantly smaller than the value of the baseline model (-2424.495). Similarly, the BIC and AIC of the final model (3703.184 and 3606.196 respectively) have also substantially improved over the baseline model's BIC and AIC values (4919.484 and 3606.196 respectively), indicating a major improvement in model fit. Hence, these improvement suggests that the relationships between cycling environment attributes and perceived safety depend on contextual factors such as the sociodemographic subgroups gender and cycling frequency, and how cyclists perceive attributes in an interaction context.

Table 4.3: Final Mixed Logit Model with significant interaction effects

Variable	Estimate	s.e.	t-ratio	p-value
$\mu_{PERSPECTIVE}$	-1.36	0.558	-2.44	0.015
$\sigma_{PERSPECTIVE}$	-7.50	1.54	-4.88	< 0.001
μ_{LANE_TYPE}	-15.0	0.346	-43.4	0
σ_{LANE_TYPE}	-2.17	0.244	-8.89	0
μ_{LANE_WIDTH}	-0.762	0.113	-6.77	< 0.001
σ_{LANE_WIDTH}	-0.769	0.289	-2.66	0.008
$\mu_{CROWDING}$	-11.6	0.745	-15.6	0
$\sigma_{CROWDING}$	-1.75	0.0957	-18.3	0
$\mu_{SPEED\_DIFFERENCE}$	-1.03	0.270	-3.81	< 0.001
$\sigma_{SPEED\_DIFFERENCE}$	-9.63	1.65	-5.84	< 0.001
ASC_1	0.223	0.0503	4.43	< 0.001
crowding*perspective	-0.773	0.128	-6.06	< 0.001
speed difference*crowding	-0.187	0.0804	-2.33	0.020
Speed difference*perspective	0.112	0.115	0.977	0.329
speed difference*lane type	0.0842	0.119	0.706	0.480
lane type*gender	0.0787	0.119	0.663	0.508
lane type*perspective	0.602	0.134	4.50	< 0.001
lane type*lane width	1.12	0.183	6.11	< 0.001
lane type*I never cycle (baseline)				
lane type* less than 1 day/week	0.526	0.209	2.52	0.0117
lane type* 2 - 3 days/week	0.603	0.172	3.50	< 0.001
lane type* 4 - 5 days/week	0.545	0.167	3.27	0.001
lane type* 6 or more days/week	0.322	0.176	1.82	0.068
Model Fit Statistics				
Number of estimated parameters	22			
Observations	3665			
Final log likelihood	-1781.10			
Rho-square (ρ^2)	0.077			
Adjusted Rho-square ($\bar{\rho}^2$)	0.066			
Akaike Information Criterion (AIC)	3606.20			
Bayesian Information Criterion (BIC)	3703.18			

Non-significant variables

Throughout the search for the optimal mixed logit model, various interaction variables were found statistically insignificant, indicating that these variables do not explain choices of respondents.

When examining variation across age groups, using the youngest cohort (18–24 years) as the reference category, none of the age-related interaction terms reach statistical significance. Accordingly, the 18–24-year group does not differ meaningfully from older cohorts with respect to the evaluation of speed differences. This indicates that age does not significantly moderate respondents' assessments of speed. In addition, no statistically significant differences between age groups are observed in their interaction with the film perspective. By contrast, the interaction terms involving crowding and lane width show some statistically significant differences between specific age categories. However, because these effects do not involve systematic differences across all age groups, and the full set of pairwise age-group comparisons is therefore not represented, these particular interaction effects are not reported in detail.

In examining gender-related differences, the mixed logit model yields several statistically non-significant effects. There is no evidence of a difference between males and females in their responses to varying speed differentials. Likewise, no statistically significant differences between these sociodemographic subgroups are observed in their reactions to variations in lane width, crowding levels, or changes in perspective.

With regard to cycling frequency subgroups, the interaction terms involving changes in perspective, lane width, crowding levels, and speed differences are also non-significant. This suggests that there is no systematic variation across cycling frequency groups in their responses to these attributes.

Furthermore, the interaction effects between speed differences and the other attributes produce several non-significant coefficients. Specifically, the interactions between speed differences and lane width, perspective, and lane type do not have a statistically significant impact on choice behavior. This implies that, on average, respondents do not adjust their responses to speed differences as a function of variations in lane width, filming perspective, or whether the facility is a one-way or two-way cycling lane.

Computing the Mixed Logit Bètas

The mixed logit Bètas indicate what the actual effect is of an attribute on the utility of an individual. To compute the values of the mixed logit Bètas, the results of the final mixed logit must be correctly interpreted using the distributions of the five random variables. Not all five random variables are similarly defined in their distribution. Lane width is defined as normal whereas the other variables are defined as lognormal (see the distributions of the Bèta of each attribute under 3.9.2). Lognormal coefficients must be interpreted somewhat differently. To be more precise mu and sigma refer to the underlying normal, not directly to β's mean/standard deviation (SD). Computing the implied means and standard deviation of the random variables yields the following table:

Table 4.4: Implied mean and standard deviation of the random coefficients β_k.

Variable	Implied mean	Implied SD
Perspective	-0.26	1.42×10^{-4}
Lane type	-3.08×10^{-7}	3.53×10^{-8}
*Lane width	-0.52	2.54×10^{-1}
Crowding	-9.31×10^{-6}	1.63×10^{-6}
Speed difference	-0.36	2.35×10^{-5}

* *normal distributed*

Inserting the output values of each attribute according to their distributions (see Table 4.4) yield the following utility function:

$$\begin{aligned} V_{1nt} = &-0.26 \cdot \text{PERS}_{1nt} - 3.08 \times 10^{-7} \cdot \text{LANE\_TYPE}_{1nt} - 0.52 \cdot \text{LANE\_WIDTH}_{1nt} && (4.1)\\ &- 9.31 \times 10^{-6} \cdot \text{CROWD}_{1nt} - 0.36 \cdot \text{SPEED\_DIFF}_{1nt}. && (4.2) \end{aligned}$$

Regarding the means and sigmas of the five (random) main variables, they largely retain their expected signs and significance. After transformation due to their lognormal distribution lane type and crowding tend to become factors with minimal influences on safety perceptions of individuals. The two other lognormal distributed variables, crowding and speed difference, do have strong negative effects, indicating that both congested conditions and greater differences in cycling speeds reduce perceived safety.

Regarding the normally distributed variable, lane width, the coefficient did become significant in this extended model, wherein the negative coefficient signals that wider lanes result in a slightly lower perception of safety. Lastly, the perspective variable remains negative and significant, indicating that viewing the scene from the overtakers' perspective is associated with reduced perceived safety.

In the context of interaction terms, the interaction between crowding and perspective shows that crowded conditions feel especially unsafe when viewed from the overtaker's perspective, likely due to encountering more cyclists during the scenario compared to the perspective from the one who gets overtaken. The negative interaction between speed difference and crowding indicates that high speed heterogeneity further worsens perceptions of safety under congested conditions. In contrast, the interaction between lane type and lane width has a strong positive effect, showing that wider lanes can significantly mitigate the negative perception associated with two-way cycle tracks. The positive interaction between lane type and perspective suggests that overtaking in two-way lanes is perceived as somewhat safer than expected.

Furthermore, the interactions between the infrastructural attribute lane type and the sociodemographic variables of cycling experience show that frequent cyclists perceive two-way lanes as less unsafe, which could reflect higher confidence and familiarity with cycling environments wherein cyclist ride in opposite directions. Finally, the interaction terms between lane type and cycling frequency are positive and significant, indicating that the negative perception of two-way cycling lanes mitigates as the weekly cycling frequency increases. Occasional cyclists (those cycling less than once per week) already perceive two-way lanes as somewhat less unsafe, and this effect strengthens among those cycling two to five days per week. Also for very frequent cyclists (six or more days per week), the effect remains positive although only marginally significant compared to the baseline group who never cycles.

4.3. Ranking of scenarios

The ranking method assesses the perceived safety of individual scenarios by treating these as distinct environments. When the questionnaire results are examined from an alternative perspective, a convergence emerges between the pairwise comparisons of scenarios and the safety ratings assigned to individual scenarios. Consequently, the scenario-based rankings can serve dually as a comparative instrument and as a validity check for the mixed logit estimation results.

The Friedman test indicated that the distribution of scores across the scenarios was not uniform. Thus, respondents rated some scenarios consistently higher or lower than others. The magnitude of the chi-square statistic (330.12) exceeds the critical value for 31 degrees of freedom (χ^2 at 0.05 = 44.99), implying strong evidence of actual differences rather than random variation. Hence, the Friedman test confirms that the differences in the mean-based ranking are statistically meaningful.

The top-rated scenarios displayed in Table 4.5 (with means ranging from 3.32 to 3.42) share several design characteristics that tend to enhance perceived cycling comfort and safety. All scenarios in this table involve two-way lane configurations, predominantly under off-peak crowding conditions, wherein cycling lane widths and speed heterogeneity vary among the scenarios. It should be noted that respondents tend to favor scenarios with lower speed differences due to their order in Table 4.5. The perspective attribute showed no consistent effect on evaluations. Overall, Table 4.5 indicates that the combination of two-way operation, lower crowding, and slightly lower speed differences during overtaking as the most favorable user perceptions of cycling conditions.

Scenario	Mean	Perspective	Lane type	Lane width	Crowding	Speed difference
1029	3.421	Left	Two-way	220 cm	Off-peak	(+) 5 kmh
1025	3.410	Left	Two-way	170 cm	Off-peak	(+) 5 kmh
1012	3.337	Right	Two-way	170 cm	Peak	(+) 10 kmh
1014	3.334	Right	Two-way	220 cm	Off-peak	(+) 10 kmh
1026	3.322	Left	Two-way	170 cm	Off-peak	(+) 10 kmh

Table 4.5: Scenarios with highest mean score

On the contrary, the lowest-rated scenarios (M = 2.03 – 2.25) in Table 4.6 are consistently characterized by one-way lane designs, mostly under peak crowding conditions. In these scenarios, wider lane widths do not seem to positively impact safety perceptions. In addition, higher speed differentials are included in most of the 5 lowest-rated scenarios.

Scenario	Mean	Perspective	Lane type	Lane width	Crowding	Speed difference
1021	2.254	Left	One-way	220 cm	off-peak	(+) 5 kmh
1022	2.226	Left	One-way	220 cm	off-peak	(+) 10 kmh
1008	2.180	Right	One-way	220 cm	Peak	(+) 10 kmh
1020	2.107	Left	One-way	170 cm	Peak	(+) 10 kmh
1023	2.032	Left	One-way	220 cm	Peak	(+) 5 kmh

Table 4.6: Scenarios with lowest mean scores

This pattern suggests that lane type and crowding levels are the dominant determinants of perceived cycling comfort when merely examining individual scenarios. One-way lanes, especially when congested, likely limit maneuverability and increase interaction stress, leading to lower safety perceptions. Attributes such as lane width and speed difference play secondary roles in shaping safety perceptions within single scenario ratings.

In addition to the mean values per scenarios, the mean values per attribute level are computed to assess whether attribute values yield large differences in the respondents' ratings. Figure 4.6 compares the mean values for each level of the five binary attributes.

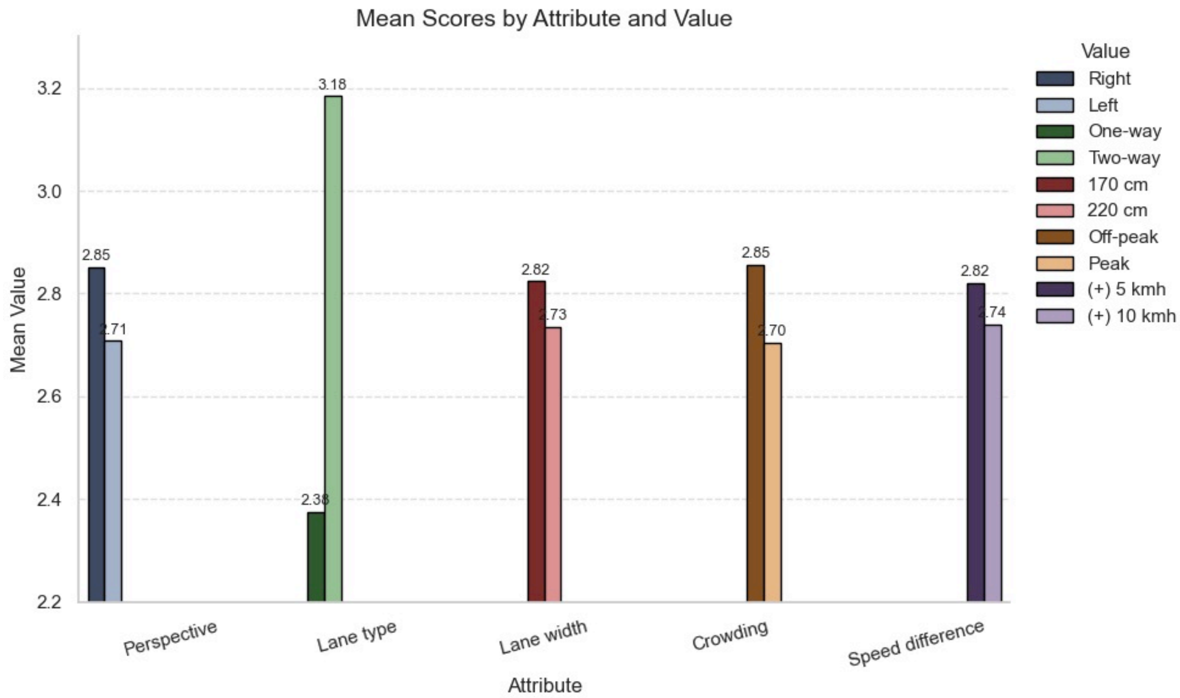


Figure 4.6: Mean scores comparison per attribute

Firstly, regarding the perspective attribute in Figure 4.6, a lower mean score can be distinguished for scenarios involving the perspective from the overtaking cyclists. This lower mean indicates that respondents perceive scenarios displaying the perspective of the person who gets overtaken as safer. Secondly, the arithmetic mean yields a significant difference between the two attribute levels of the lane type attribute, where scenarios involving two-directional cycling lanes obtains a higher mean than its one-directional counterpart, indicating lower safety perceptions for scenarios containing one-directional cycling tracks. Zooming in on the lane width's attribute values, an arithmetic mean with marginal variation can be observed. Although its effect is not substantial, scenarios containing narrower lanes are perceived as marginally safer than scenarios with wider lanes. Moreover, scenarios covering off-peak hour crowding conditions signal a safer cycling environment for respondents. Lastly, questionnaire participants slightly prefer scenarios which display lower speed differences during an overtaking manoeuvre in terms of safety.

4.4. Scenarios' attribute values within the utility function

Since survey participants might react differently to differently formulated questions, it would be interesting to see whether respondents did react differently to the forced choice question *'Which scenario feels safer?'* and the rating question *'How safe would you rate this scenario?'* that were stated below each video-based choice set. Therefore, the utility function , which was drafted based on the Bèta values of the mixed logit model, can serve as formula wherein the values of the scenario ranking are inserted, and a final utility per scenario is computed. These final utility values can be compared to the each scenario ranking and could confirm whether respondents react consistently among the different question per choice set. Inserting the values of the five highest rated scenarios into the utility function, and subsequently applying the standard binary logit formula yield the utility and choice probability values presented in 4.7.

The comparison between the mean scenario rankings and the corresponding utilities reveals a somewhat consistent pattern between responses of the forced choice and the rating questions. In the utility composition, changes in perspectives, lane width, and speed differences move utilities. Across the five highest-rated scenarios, utilities fall within the range of −0.26 to −0.88, indicating that their is a moderate variability of the utilities among these scenarios. However, if the ranking was based on the utility of these five scenarios, the order would slightly change compared to the mean-based ranking. In addition, the utility values for the highest-ranked scenarios remain negative, which is consistent with the negative signs of the key coefficients of the mixed logit model. Thus, when merely considering the highest ranking scenarios, respondents are consistent when responding to the different questions per choice set.

Table 4.7: Utilities and choice probabilities of the highest ranked scenario

Highest ranked scenarios	Mean	Utility	Choice probability
1029	3.421	-0.78	0.46
1025	3.410	-0.26	0.59
1012	3.337	-0.36	0.56
1014	3.334	-0.88	0.44
1026	3.322	-0.62	0.50

Considering the lowest-rated scenarios, the utilities become more negative (e.g., −1.14 for Scenario 1022), which is consistent with the mixed logit model's prediction that combinations of an overtaking perspective with larger speed differences strongly reduce perceived safety. Interestingly, some scenarios with relatively similar utilities across the high and low groups (e.g., −0.78 appearing in both sets) highlight that utility values alone are not strict indicators of absolute preference but reflect the additive impact of attribute levels in relation to each other. The mean scores, however, show clearer separation between the best and worst scenarios, which suggests that respondents reacted stronger to the rating question compared to the forced choice question. This could be the result of the difference of both analysis methods. The mixed logit model focuses on estimating the marginal effects of attributes rather than replicating raw scenario rankings. Computing the final utilities of the five lowest rated scenarios lead to the following outcomes:

Table 4.8: Lowest ranked scenario utilities and choice probabilities

Lowest ranked scenarios	Mean	Utility	Choice probability
1021	2.254	-0.78	0.46
1022	2.226	-1.14	0.37
1008	2.180	-0.88	0.44
1020	2.107	-0.62	0.50
1023	2.032	-0.78	0.46

Subsequently, the choice probabilities are comprehensively visualized in Figure 4.7. The figure illustrates how each scenario's probability of being chosen varies as a function of its utility difference relative to the baseline scenario. All points fall directly on the logistic curve, confirming that the probabilities were correctly derived from the binary logit model. The green and red-marked dots represent the highest and lowest mean-based ranked scenarios respectively. Scenarios with larger positive utility differences, e.g., 1025 and 1012, lie on the upper portion of the curve and therefore indicate the highest choice probabilities, approaching 0.6. These scenarios outperform the baseline due to relatively higher utilities, meaning they are more likely to be selected when compared with the baseline alternative (scenario 1018). In contrast, scenarios with utility values close to the baseline, such as 1026, show choice probabilities around 0.5, indicating no clear preference when compared to the baseline. These mid-range probabilities reflect only marginal differences in utility. The lower part of the curve contains the scenarios whose utilities fall below that of the baseline, resulting in substantially lower choice probabilities. Scenarios such as 1022 and 1008, which exhibit the largest negative utility differences, achieve probabilities closer to 0.35–0.44. This signals that they are notably less likely to be chosen. Scenarios such as 1021, 1023, 1029, and 1008, cluster closely together, indicating very similar relative performance with respect to the baseline.

Zooming in on individual scenarios, for instance scenario 1025, presenting the highest choice probability (0.59) in Figure 4.7, simultaneously identifies as one of the highest ranked scenarios in the mean-based ranking. This scenario is captured from the overtaker's perspective on a two-directional (1.7 m width) cycle track with overtaking speeds of + 5 km/h during off-peak hours. On the contrary, scenario 1022 is presented as the scenario with the lowest probability in choices (0.37). Aligning with the low probability, this scenario is included in the lowest mean-based ranked scenarios. 1022 entails a scenario visualized from the overtaker's perspective, on a one-directional (2.2 m) cycling track with overtaking speed differences of +10 kmh during off-peak times.

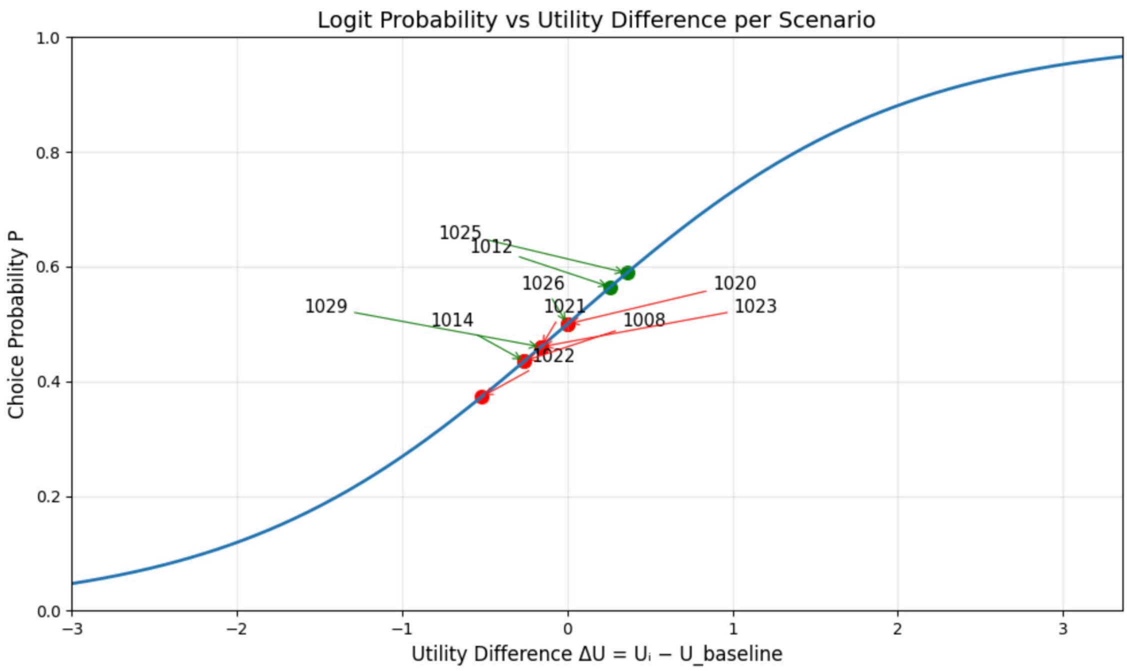


Figure 4.7: The choice probabilities of the five highest & lowest ranked scenarios

Overall, the values of the utilities and choice probabilities somewhat correspond to the scenarios' positions within the mean ranking, indicating that respondents are to some degree consistent in answering to different question types per choice set. In addition, the utilities between the highest ranking and lowest ranking scenarios show a pattern (low ranking often translates to lower utility) that also confirms this consistency. In addition, examining two distinct scenarios (1025 & 1022) yields a clear consistent difference in both the mean-based ranking and the choice probabilities, with scenario 1025 ranked significantly higher on all aspects compared to scenario 1022. Still, the scenario ranking would be looking differently when only accounting for the final utilities per scenario, signifying that not each scenario is rated consistently among both question types.

5
Discussion & Implications

This chapter contains a discussion on the results and their implication towards policies. Section 5.1 briefly restates the research's aim. Additionally, this section involves the interpretation of the results of Chapter 4. Section 5.2 involves the scientific contribution this research yields. Section 5.3 provides policy makers the policy relevance of this study and several policy recommendations. Lastly, section 5.4 presents several limitations of this research and what these can imply regarding future research.

5.1. Discussion of results

This section discusses the questionnaire's findings. Firstly, the aim is briefly stated. Subsequently, the core results are discussed. Furthermore, the effects of the interaction variables and the variety among demographic subgroups are stated. Additionally, the results of the mixed logit are compared with the outcomes of the scenario ranking method.

5.1.1. Research aim

The aim of this research was to investigate to what extend cyclists are subjectively affected by differences in cycling speeds within bicycle-only environments. To examine this, a literature study was performed to gain insights into all the factors influencing perceived safety. Subsequently, a video-based questionnaire was constructed wherein video captured the effects of speed differences in different situations. Next, the results were analyzed with the mixed logit model to check the exact impact on safety perceptions.

5.1.2. Effects of core results

The Mixed Logit model provided a thorough understanding of how different cycling environment attributes affect safety perception. Within the context of speed heterogeneity, the mixed logit model reveals that this attribute does impact safety perceptions of individuals. Furthermore, the perspective variable (viewpoint of the overtaking cyclist vs. the overtaken cyclist) was negative and significant, suggesting that participants felt less safe when observing situations from the overtaking cyclist's viewpoint. This likely originates from experiencing the same situations from an perspective that cycles at higher speed. With regards to lane types, two-directional cycling tracks are perceived as marginally less safe than one-way lanes. Although its minimal effect on utility, this finding aligns with the an expected thought that two-way lanes create more potential conflicts between cyclists traveling in opposite directions, reducing the feeling of control and predictability. Kazemzadeh (2025) underscored this with stating that the direction of encounters matters, which signifies that meeting other users as perceived as more unsafe than overtaking them. In addition, higher levels of crowding had a very small negative effect, showing that congested conditions do lower perceived safety. Uijtdewilligen et al. (2024) & Berghoefer and Vollrath (2022) confirm that high crowding levels were seen as a factor which yields a negative impact on the feelings of safety. The negative coefficient likely reflects discomfort from a reduction in available space for possible deviation in case of potential collisions or near misses.

Curiously, lane width was statistically insignificant in the baseline model, implying that variations between 170 cm and 220 cm did not strongly affect perceived safety in isolation. This might be a result of opting for a difference of 0.5 m between both attribute values. Visually, the 0.5 difference is being mitigated resulting that this variation is not clearly observable for respondents. Still, its role became more apparent once interactions were included in the extended model. In the final model, the negative coefficient indicates that wider lanes slightly impact perceived safety negatively. Oddly, respondents specified that narrower cycling lanes are perceived as safer. Looking at previous studies the outcomes of this mixed logit model do not correspond with previous studies, which state that wider cycling lanes contribute positively to a high subjective safety of cycling lanes Stülpnagel and Binnig (2022b).

5.1.3. Effects of interactions

Besides the main effects on safety perceptions, the mixed logit also included several statistically significant interaction effects. The negative interaction between crowding and perspective implies that crowded conditions feel especially unsafe when viewed from the overtaking cyclist's perspective. This likely reflects the overtaker's need to navigate through situations where cycling density is high, and therefore increasing cognitive and physical burden. Additionally, the negative interaction between speed difference and crowding indicates that high speed heterogeneity further amplifies unsafeness in congested situations. Thus, the combination of fast and slow cyclists in crowded locations creates a particularly unsafe perception.

In terms of positive interactions, the positive interaction between lane type and lane width demonstrates that wider lanes can partly offset the negative perception of two-way tracks. Thus, increasing lane widths can mitigate the high levels of unsafeness associated with two-directional cycling lanes. Moreover, the positive interaction between lane type and cycling frequency reveals that frequent cyclists perceive two-way lanes as less unsafe compared to those who non-cyclists. Cyclists who cycle regularly likely have more experience in anticipating situations and are more aware of their surroundings during cycling. These could help them experience these situations more comfortably.

The various interactions confirm that cyclists' perceptions are context-dependent instead of remaining constant over various situations. Conclusively, the four key factors influencing perceptions do not act as solo attributes. Thus, their influence depends on how they interact with each other and the demographic characteristics of the sample.

5.1.4. Demographic effects

The descriptive analysis entails several key patterns concerning how cyclists perceive their surroundings and how these perceptions vary across demographic and behavioral groups.

Outcomes of the statements questions indicate that females are impacted easier by high speeds in cycling and surrounded by many Fatbike compared to males. In addition, people aged 65 years and older are more sensitive to high speed environments and locations wherein many cyclists on Fatbikes are present. In other words, females and older respondents tend to report stronger feelings of unsafety regarding situations wherein surrounding cyclists are riding with high speeds or the presence of Fatbikes. No notable variation among respondents with different weekly cycling frequencies was found. Furthermore, all three sociodemographic subgroups do consistently (partially) agree with feeling unsafe in both situations (when cyclists drive at high speeds & when many Fatbikes are nearby). Pointing towards a consistent negative response regarding these two statements among all demographic subgroups.

Regarding the demographic subgroups within the mixed logit model, its outcomes indicate that no significant differences can be observed between both genders and the various age groups in reaction of one of the five attributes. Compared to the cycling frequency baseline group (non-cyclists) all other frequency-based groups are perceive more safety when cycling in two-directional ways. This tend to be an expected outcome since frequent cyclists also encounter two-directional cycling lanes more often than infrequent cyclists, and thus experience higher familiarity with this attribute level compared to non-cyclists. Generally, people tend to perceive somewhat as unsafer when it is unfamiliar to them. Hence, this expected results.

The results regarding the demographic subgroups align with prior research that associates higher sensitivity to perceived risk. Groups with less frequent cycling and female respondents, who are generally found to be more risk-averse in traffic settings. This aligns with outcomes that the female gender is stronger affected in terms of safety perceptions. Ayad et al. (2024). Additionally, older aged groups are more sensitive to lower levels of safety perceptions. These finding were also highlighted by previous studies of Haustein and Møller (2016) & Uijtdewilligen et al. (2024). Furthermore, respondents who cycle more frequently displayed slightly lower levels of perceived unsafety, suggesting that familiarity and confidence may mitigate perceived risk.

Where the mixed logit does not yield a statistically significant variation among most of the sociodemographic groups regarding most of the attributes, the demographic subgroups do indicate variation when responding to the cycle speed and Fatbikes statements. This implies that perceived cycling safety is shaped not only by infrastructure and traffic factors, but also by individual characteristics.

5.1.5. Comparison with scenario rankings

Most outcomes of the scenario ranking align with the results that the mixed logit model produced. However, there are certain noteworthy variations between both outputs. Scenarios rated highest in safety perception frequently involved off-peak conditions, slightly lower speed differences, and consistently two-directional lanes. Conversely, the lowest-rated scenarios in terms of subjective safety combined one-way configurations with high crowding and large speed differences. Interestingly, while the mixed logit model found two-directional lanes to slightly reduce perceived safety overall, the mean ranking results suggest a stronger difference between the lane configuration. Here, scenarios involving one-way cycling lanes are consistently perceived as less safe. In the context of the ranking, the high scoring two-directional based scenarios are regularly combined with lower crowding levels and lower-speed differences leading to a safer ratings by respondents. This difference can be explained regarding a difference in question type that were used as input for each method. Where responses of the mixed logit were based on the forced choice questions, results of the scenarios ranking are grounded on a rating questions. This implies that survey participants were responded somewhat differently regarding a comparison question and a ranking questions.

5.1.6. Overall interpretation

The speed heterogeneity values in both the mixed logit and the ranking analysis yield slight differences. In both methods, speed differences have strong negative effects on the safety perception of cyclists in a variation of scenarios. Hence, greater differences in cycling speeds reduces perceived safety. In addition, the overall results indicate that perceived cycling safety is driven by interactions between infrastructure characteristics, traffic conditions, and individual demographics. The mixed logit model revealed that, besides speed heterogeneity, the filming perspective and the lane width mainly influence how safe cyclists feel in different situations.

5.2. Scientific contribution

The results provide a first insight into the actual impact of speed heterogeneity on safety perceptions on cyclists in the context of bicycle-to-bicycle interactions. Previous studies have merely researched this impact regarding bicycle-to-car interactions. This study extends this area of research towards assessing the impact of speed differences in cyclist-only environments. In addition, the findings demonstrate that crowding, speed differences, and lane type are not only significant determinants on their own but also exhibit important interaction effects, particularly the amplified negative impact of speed differences under crowded conditions and the moderating effect of wider lanes on two-way cycling tracks. Furthermore, by using video-based stated preference experiments, this study captures dynamic overtaking situations that traditional survey-based or static-image methods overlook, offering a more realistic assessment of how cyclists experience speed heterogeneity in practice. The identification of sociodemographic heterogeneity, such as greater sensitivity among less frequent cyclists, adds a view that enriches existing literature. Overall, the study strengthens theoretical and methodological foundations for modeling subjective safety and provides evidence-based insights that can guide future transportation research and policy design.

5.3. Policy Implications

These findings also have practical implications for urban planners and policymakers. Given that the results imply that speed heterogeneity indeed has an impact on safety perception, efforts should be made to ensure that speed differences between cyclists are either contained within current cycling speed standards, or mitigated when the situation requires this. Potential ways to do so are subdivided between infrastructural and societal measures. With each recommendation, it should be emphasized that higher levels of subjective safety do not necessarily imply decreasing numbers of actual accidents on cycling infrastructure.

Introduce signage to indicate slow-paced zones
Municipalities should implement clear and consistent signage to designate slow-paced cycling zones in areas with high interaction intensity, such as city centers, school surroundings, or corridors with decreased visibility e.g., tunnels or winding cycling tracks. These visual pointers help to nudge cyclist behavior and reduce speed heterogeneity among cyclists. The signage should be integrated into the broader way-finding and design guidelines of the cycling network to mark the transitions between calm and faster zones. However, additional objects and signage along cycling tracks could introduce further distractions or add new potential hazards which could in turn again decrease the level of perceived safety in certain locations.

Construct multi-paced lanes where space permits
The strong effects of speed heterogeneity underline the importance of designing cycling infrastructure that can accommodate varying cyclist speeds safely. This could include a segregation between faster and slower bicycle types, such as Fatbikes or e-bikes. Thus, this could lead to less conflict between faster-paced cyclists and cyclists driving in a slower pace. However, introducing such infrastructural adaptions tends to be a costly investment, so cost-benefit trade-offs must be made carefully.

Educational awareness in schools
It is advised that municipalities should increase awareness regarding speed differences on cycling lanes in cycle-dense environments and its impact on the feelings of safety of other cycling lane users. By promoting understanding and mutual respect among cyclists, introducing such campaigns can increase awareness under cyclists who regularly cycle on faster bicycles (e.g., Fatbikes). Hence, increasing awareness among e-bike users can indirectly help to mitigate feelings of unsafety, especially for women, older adults, and less frequent cyclists. In this context, it is recommended to align these campaigns with non-governmental organizaitons(e.g., Fietsersbond) to spread consistent behavioral norms.

Set up (online) reporting points for locations with low levels of subjective safety
Municipalities should establish and promote accessible (online) reporting locations (similar to Meldpunt Fietsveiligheid of the Fietsersbond) where cyclists can indicate specific environments they perceive as unsafe. This setup allows residents to share feedback on infrastructure and traffic interactions that negatively affect their sense of safety. Integrating such reporting points would provide continuous, real-time insights into user perceptions of cycling lanes. It should be noted that these points of data collections should be as inclusive as possible, since older-aged, one of the groups which is more sensitive regarding safety perception, tend to have difficulty with accessing digital sources.

By implementing these measures, municipalities can contribute to a transition towards sustainable urban mobility, which can increase the share of the bicycle as mode choice.

5.4. Limitations & further research

Although this study provides valuable insights into perceived cycling safety and the factors influencing it, several limitations must be acknowledged to contextualize the findings and guide future research efforts.

First, the experimental design included only a limited number of attributes varying in its values (lane type, lane width, crowding and speed difference). While these were selected based on their significance in literature and in the safety experts' opinion, other key factors such as surface quality, visibility, overtaking behavior and intersection design were not incorporated as varying attributes. Additionally, the use of short point-of-view videos to represent overtaking situations simplified complex real-world dynamics. The visual material did not entail elements such as background noise or surrounding awareness. The exclusion of these attributes means that the model captures only a subset of the variables that shape cyclists' safety perceptions, which could slightly limit the validity of the findings.

Secondly, this research relied on stated preference data gathered through video-based experiments rather than revealed preference data. Although this approach allows for more precise control over the tested attributes and facilitates the examination of specific scenarios, it captures scenario-based perceptions rather than actual situations. Respondents' subjective evaluations may differ from their real-world responses, where additional contextual and emotional factors, such as varying weather variables, different infrastructural and traffic conditions, or dissimilar interactions with other road users also play a role in perceived safety.

Lastly, in the questionnaire perceptions were measured at one point in time, hence providing merely a snapshot rather than an continuous understanding of how perceived safety changes with experience or infrastructure modifications. Here, longitudinal or repeated measures research could reveal how users adapt to other or improved cycling environments. Additionally, since respondents evaluated multiple scenarios within the same survey, potential learning or fatigue effects could have influenced the consistency of responses, despite efforts to limit the number of video-based questions to 6.

Further research should explore revealed preference data as validation of stated preference data. To strengthen validity, this additional method could complement stated preference experiments with revealed preference data or real-world behavioral observations. For example, interview with cyclist who just experienced overtaking situation with large speed differences. In this context, speed measurements or video analytics of interactions on actual cycle tracks could be used to validate or contrast perceived safety judgments. Combining perception-based assessments with real-life data would allow researchers to distinguish between perceived and experienced safety outcomes. Moreover, new research should expand the range of attributes included in the choice experiment. This would enable a more comprehensive insight into of the factors that altogether influence perceived safety. Moreover, since this research only contains snapshots of one point in time, longitudinal research could explore how perceived safety evolves as cyclists gain experience or as infrastructure changes occur in cities. Tracking perceptions before and after the implementation of new cycling measures would provide valuable evidence on the effectiveness of such interventions.

Overall, while this study provides an important foundation for understanding the impact of speed heterogeneity on perceived cycling safety, addressing these limitations would add a more comprehensive insight into how cyclists experience safety within the active mode of cycling.

6 Conclusions

This research aimed to find an answer to the following research question: ”To what extent does heterogeneity in cycling speeds affects safety perceptions of cyclists in urban dense environments, and how can these effects inform targeted improvements for Dutch municipalities?”. To find an answer to this question a combination of a literature study, a video-based questionnaire, and a mixed logit have been applied.

The effects of speed heterogeneity can be measured using a stepwise approach by first creating a conceptual model of attributes that all impact the subjective safety of an individual. This yields an comprehensive overview of all relevant attributes that influence levels of safety perception. By opting for a video-based questionnaire, the effect of speed differences can accurately be shown to the respondents, who will be faced with forced choice questions. Subsequently, a panel-based mixed logit model allows for assessing and quantifying the impact of speed heterogeneity of the level of perceived safety.

The literature study and discussions with safety experts identified four categories of factors influencing cyclists' safety perceptions: infrastructure attributes, traffic conditions, environmental variables, and individual characteristics. Infrastructure-related factors include road surface quality, gradients, two-directional lanes, lane width, intersections, roadside objects, and curb forgiveness. Traffic conditions such as crowding, variation in bicycle types, overtaking behaviour, and (heavy) motor traffic also play a role. Environmental influences include wind, daylight, and precipitation. Finally, individual characteristics, such as cycling experience, age, gender, and geographical context, affect perceived safety. Overall, these factors shape how cyclists evaluate safety on cycling infrastructure.

The mixed logit model confirms that higher speed differences decreased safety perception of cyclists. However, its influence also depends on other attributes. Two-directional cycling tracks are perceived as slightly less safe than one-way lanes. Furthermore, peak hour conditions marginally lower perceived safety. Speed differences in crowded conditions further amplify unsafe feelings. Regarding variances between sociodemographic groups, frequent cyclists perceive two-way lanes as less unsafe compared to non-cyclists. Hence, the influence of speed heterogeneity depends on how it interacts with other attributes such as traffic, infrastructural, individual characteristics.

Regarding the final part of the research question, four policy recommendations can be offered to municipalities. First, in terms of societal measures, municipalities should raise awareness in public settings, such as schools, about the safety implications of speed differences on crowded cycling lanes. They should also provide accessible (online) platforms where cyclists can report locations they perceive as unsafe. Second, concerning infrastructural measures, municipalities should introduce clear and consistent signage to indicate slow-paced cycling zones, particularly in areas with high interaction intensity such as city centers, school environments, and locations with limited visibility. Additionally, where spatial conditions permit, municipalities should consider implementing multi-paced cycle lanes that allocate separate space for faster and slower cyclists. Together, these measures can improve subjective safety on cycling lanes identified by cyclists as unsafe.

This research reveals that speed heterogeneity is a key factor shaping cyclists' safety perceptions in dense urban environments. The mixed logit model confirms that larger speed differences reduce subjective safety, and that this effect is moderated by infrastructure, traffic conditions, and sociodemographic characteristics. The findings demonstrate that speed heterogeneity cannot be treated in isolation. This study contributes to the literature by deepening the understanding of cyclists' safety perceptions and offering a methodological approach to assess the impact of speed heterogeneity. It also provides Dutch municipalities with evidence-based guidance for targeted interventions. Future research could expand the attribute set and apply longitudinal designs to examine how perceptions evolve over time. Ultimately, this study emphasizes that addressing speed heterogeneity is essential in shaping inclusive cycling environments where every cyclist feels safe.

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A

Appendix A - Full Questionnaire

Survey Questions

Section I. Sociodemographic questions

1. What is your age?
    - 17 years or younger
    - 18–24 years
    - 25–29 years
    - 30–39 years
    - 40–49 years
    - 50–64 years
    - 65–74 years
    - 75 years or older
2. What is your gender?
    - Male
    - Female
    - Other, namely: ________________
    - Prefer not to say
3. Do you wear contact lenses or glasses?
    - Yes
    - No
4. Do you have difficulty distinguishing colors?
    - Yes
    - No
    - I don’t know
5. How often do you cycle per week?
    - I never cycle
    - < 1 day
    - 1–3 days

- 4–5 days
- 6+ days

6. What type(s) of bicycle do you ride weekly?
   - ☐ Regular bicycle
   - ☐ Road bike
   - ☐ Regular e-bike
   - ☐ Fatbike
   - ☐ Cargo bike
   - ☐ Speed pedelec
   - ☐ Other ________________

7. In which city/town do you currently live?

   ____

Section II. Video-based questions

8. Which scenario felt safer? (Choose one)
   - Scenario A
   - Scenario B

9. How safe did you feel in scenario A?
   - Very unsafe
   - Somewhat unsafe
   - Neutral
   - Somewhat safe
   - Very safe

10. How safe did you feel in scenario B?
    - Very unsafe
    - Somewhat unsafe
    - Neutral
    - Somewhat safe
    - Very safe

Section III. Statements & Follow-up

11. I feel unsafe when people ride fast on the bicycle path.
    - Strongly disagree
    - Somewhat disagree
    - Neutral
    - Somewhat agree
    - Strongly agree

12. I feel unsafe when there are many fatbikes present on the bicycle path.
    - Strongly disagree
    - Somewhat disagree

- Neutral
- Somewhat agree
- Strongly agree

13. Which factors influenced your feeling of safety during the videos?

- ☐ Oncoming cyclists
- ☐ Narrow sidewalk
- ☐ Crowded bicycle path
- ☐ Presence of car traffic
- ☐ Large speed differences on the bicycle path
- ☐ Parked cars along the bicycle path
- ☐ Narrow bicycle path
- ☐ High curb
- ☐ Presence of bus traffic
- ☐ Other ________________