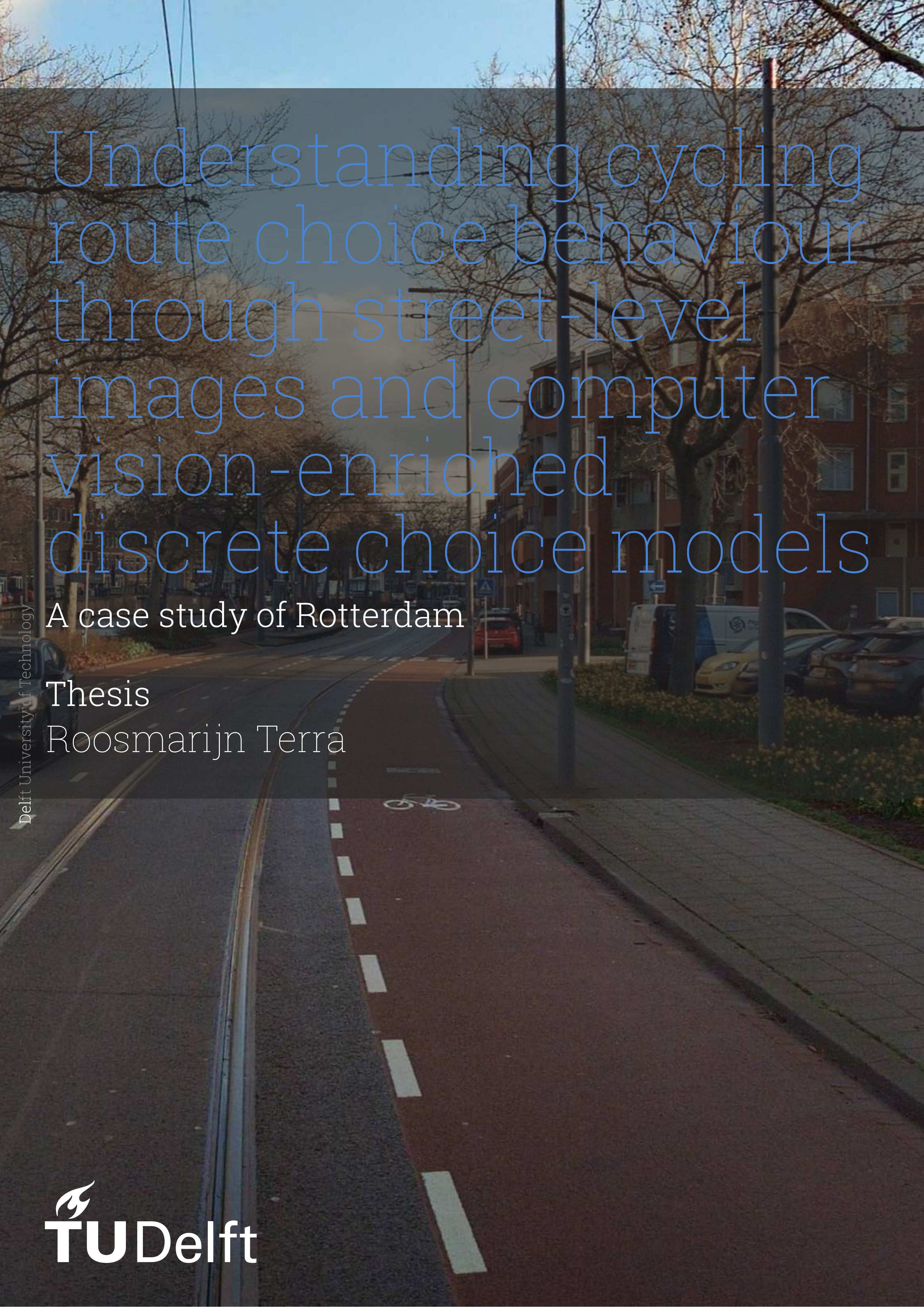

Understanding cycling route choice behaviour through street-level images and computer vision-enriched discrete choice models

A case study of Rotterdam

Thesis

Roosmarijn Terra

Delft University of Technology

Understanding cycling route choice behaviour through street-level images and computer vision-enriched discrete choice models

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by

Roosmarijn Terra

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Thesis committee:	Prof. dr. Oded Cats,	TU Delft, Chair
	Dr. Sander van Cranenburgh,	TU Delft, supervisor
	Ir. Francisco Garrido Valenzuela,	TU Delft, supervisor
	Ir. Kevin Su,	Gemeente Rotterdam, supervisor
	Ir. Zoë peters,	Gemeente Rotterdam, supervisor

Preface

About a year ago, I started thinking about what I wanted to do for my thesis. During my studies, I took many interesting courses, especially machine learning, optimisation and choice modelling. So then I came across Sanders' page on the university site and saw that he was doing research on the combination of machine learning and choice modelling and I thought he might have an interesting thesis subject. He told me he was doing research on measuring liveability in Delft and Rotterdam using street view photos, and I immediately got excited. After all, this is where machine learning, choice modelling, spatial analyses and social relevance came together. And I could study at the municipality of Rotterdam, so perfect. Unfortunately, I also had a heavy concussion at the time due to a cycling incident in Rotterdam (so this thesis subject was meant to be). Starting right away was not an option. Happily I was finally able to start in May.

In the beginning, I found it a challenge to find a good research gap, but two meetings with Francisco solved it quickly. I was mostly working at the municipality where the atmosphere was good, the view was nice, close to my home, lots of available data, and my supervisors and others were also very helpful. And they involved me by being invited to team days, sports days and other activities. With help from my supervisor Kevin, I could present my thesis proposal and midterm to different teams, such as team data, cycling, road safety and a road design team. This was very useful to get to know people working on overlapping topics to see what is already going on.

At the university, there were other students working on the topic of perception of the public space. Sander organised monthly meetings with all the graduating students to catch up on the topic. It was very useful to see what others were working on. Oded organised the public transport lab which was fun to listen to several presentations from other TIL and TP students. Francisco helped a lot by creating a survey website, and it was also great that I could use the panel company Cint so that the results would be representative and significant. In addition, I could contact Sander and Francisco for more in-depth questions and Sander took on the task of training the cv-dcm model. The weekly meetings with Kevin (and sometimes Zoë), and the monthly university meetings with Francisco and Sander were also enjoyable. I usually left with more confidence about my thesis than I arrived. All in all, thank you for the guidance! Also, a big thank you to friends, family and housemates. The last month especially, I did find it tough at times, but they helped me with some tea and a sporadic glass of wine through it. I found the individual aspect and the report writing most challenging. But overall I liked it. What I enjoyed most was collecting and analysing data and chatting with people about the subject.

Roosmarijn Terra
Delft, December 2024

Summary

This thesis investigates cycling route preferences, with a focus on the cycling environment. Cycling offers many benefits, including better health, improved accessibility, enhanced sustainability, and greater liveability. Nevertheless, the city of Rotterdam faces challenges in relation to cycling such as rising cycling accidents, infrastructure pressure due to increasing cyclist numbers, and the lack of perceived safety of cyclists. To promote cycling and guarantee a positive cycling experience, the study aims to provide insights into cycling environments that align closely with the preferences of cyclists.

Previous studies that conducted a stated choice experiment have primarily relied on textual representations or generated images of cycling environments to evaluate preferences. Yet, such methods are often inadequate, as textual descriptions are challenging for individuals to interpret, leading to inaccuracies. While research using real-world images has highlighted the influence of cycling environments on perceptions, limited studies have explored how cycling environments influence preferences for cycling routes. Visualising cycling environments facilitates a deeper understanding of individuals' preferences regarding cycling environments in the context of cycling route choices. A recently proposed model incorporates computer vision into a traditional discrete choice model to accommodate choice tasks involving numerical attributes and images. This model is referred to as the computer vision-enriched discrete choice model (cv-dcm).

The cv-dcm is applied using a stated choice experiment to gain a better understanding of cycling route preferences. In this experiment, respondents were presented with a series of choice tasks where they had to choose between two cycling routes. Each route was defined by three attributes, including commute time, number of traffic lights, and the cycling environment, the latter visualised using street-level images. To ensure consistent responses, participants were asked to imagine they were cycling home from a daily activity. They were instructed to assume they were cycling alone, not in a hurry, and that weather conditions were constant, with the image representing the visual characteristics of the entire route. An example of the visual representation of the stated choice experiment is illustrated in Figure 1.

An image analysis before the experiment was done to ensure that all characteristics of different cycling environments were visible in the stated choice experiment. Consequently, the model was able to effectively predict all different cycling environments. Furthermore, the image analysis enabled the ranking of images, supporting the use of an efficient design, which is typically more advantageous than other experimental designs. This approach improves trade-off insights and reduces parameter standard errors. 6,500 unique street-level images were used in the stated choice experiment. The combination of an efficient design with a substantial quantity of real images for the prediction of choice behaviour represents a novel approach.

The cv-dcm relies on a neural network, which can make interpretability challenging. To address this, a comprehensive data collection process was conducted to identify specific cycling environment attributes. This approach enabled the investigation of how these attributes influence predicted utility scores and allowed for route choice estimation using a traditional discrete choice model, where the impact of each attribute is isolated.

The results demonstrate that the cv-dcm outperforms traditional discrete choice models by effectively capturing image-based attributes that influence cycling route choice. This approach provides valuable insights into how cyclists perceive different cycling environments. The cycling environment was rated as the most important factor in route choice, rated three times higher, highlighting its crucial role in

cyclists' preferences. Additionally, the cv-dcm revealed that green and open environments with separated cycling lanes are highly valued by cyclists, while urbanised areas with mixed-traffic roads or industrial surroundings are less preferred. The spatial distribution of utility scores further highlighted a preference for low-density, recreational areas over high-density, urban environments. The cv-dcm also effectively identifies differences in utility between cycling infrastructure characteristics, such as type, width, colour and pavement, which can be very valuable for evaluating the impact of cycling infrastructure renovations on perceived cycling experience. The discrete choice model provided insights by isolating the effects of specific attributes on route choice. Positive influences on route choice include separated cycling lanes, greenery, and water, while car parking, houses, clinker pavement, tram lines, and industrial areas have negative impacts. Notably, on average, cyclists are willing to take a detour of approximately 1.5 minutes to cycle on a separated cycling lane instead of mixed-traffic roads for a cycle trip of approximately 11 minutes. The latent class analysis demonstrated that older individuals exhibit different preferences with regard to cycling routes as they place a greater importance to the cycling environment than younger individuals.

This study represents a significant contribution to the integration of computer vision into discrete choice modelling, providing policy makers with a powerful tool for the evaluation and design of cycling environments. By understanding the attributes that cyclists value, this study can assist policymakers in creating environments that promote cycling.

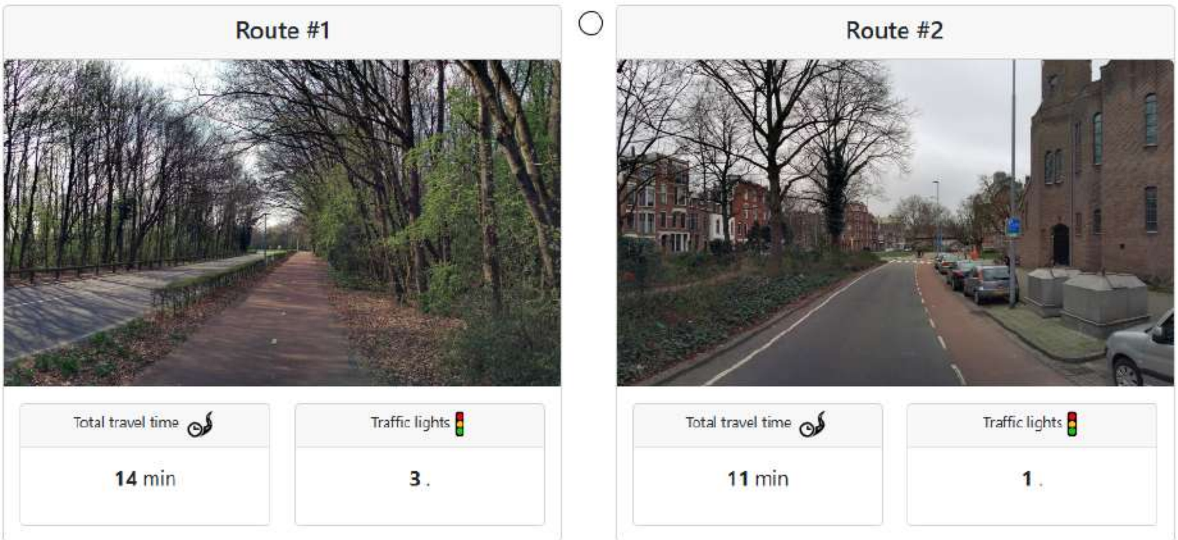


Figure 1: Example of a choice situation

Contents

List of Figures

List of Tables

1 Introduction

1.1. Background

1.1.1. Benefits of cycling

The Netherlands is a country with a high level of cycling activity. The number of kilometres cycled has increased by 23% over the period 2000 - 2022, and this trend is expected to continue (KiM, 2023). There are numerous advantages to this high level of cycling activity; it is beneficial for health and contributes to many other goals, including accessibility, sustainability and liveability (Dutch Cycling Embassy, 2018). The 2015 Paris Climate Agreement set a target to reduce CO2 emissions by at least 40% by 2030 (I&W, 2020). Achieving these climate goals underscores the importance of sustainable mobility solutions, such as cycling (European Union, 2023). Cycling also addresses health and economic challenges. In Rotterdam, common health issues such as obesity and diabetes can be mitigated through increased cycling activity (Gemeente Rotterdam, 2019a). Moreover, in neighbourhoods facing economic challenges, the high costs of car ownership and public transportation create barriers to mobility (Gemeente Rotterdam, 2019b). As a cost-effective alternative, cycling improves accessibility and promotes social inclusion.

1.1.2. Challenges of Rotterdam

The growing number of cyclists in Rotterdam places substantial pressure on the Rotterdam's cycling infrastructure, which is caused by significant population growth and the rising demand for sustainable transport. Over the past decade, Rotterdam's population has grown by 44,000 residents, an 8% increase between 2013 and 2023, with further growth expected (CBS, 2024c). During the same period, the number of cyclists has increased with a 60% (Gemeente Rotterdam, 2019b). Currently, 62% of all movements in Rotterdam are made by bicycle, on foot, or via public transport, reflecting the city's shift toward sustainable mobility (Gemeente Rotterdam, 2019a). The number of cycling accidents has been on the rise for several years, probably due to the increase in bicycle use (Gemeente Rotterdam, 2019b). As more persons start cycling, it is anticipated that the number of cycling accidents will continue to rise (Gemeente Rotterdam, 2019b). In 2022, over 1600 cyclists in Rotterdam required first aid following single-vehicle cycling accidents. This equates to three to four incidents per day, with these numbers representing only those incidents that were reported by first aid (Fietsersbond, 2023). It is likely that there are many more accidents that go unreported.

Furthermore residents of Rotterdam frequently perceive a lack of safety in the city's traffic. The municipality initiated a survey conducted in 2019, which enabled residents to indicate the locations they considered unsafe. This resulted in the identification of over 7000 locations within a three-week period (Gemeente Rotterdam, 2023). The survey revealed that 35% of the unsafe locations reported were related to the environment, 38% to behaviour and 27% to both environment and behaviour (Gemeente Rotterdam, 2023). This suggests that there is considerable room for improvement in terms of the perceived safety. It also demonstrates that the cycling environment influences a significant impact on the perceived safety of cyclists. The environment includes for example the cycling infrastructure, built environment and the maximum speed of motorised vehicles. Behaviour includes the extent to which individuals engage in anti-social driving, exceed speed limits, make loud noises or drive across cycling lanes.

1.1.3. Understanding cyclists preferences

While perceived safety is an essential component, it represents only one aspect of the overall cycling experience. Cyclists' experiences are also influenced by for example comfort and aesthetics. Therefore, the focus shifts from perceived safety to the overall perceived cycling experience. Currently, the assessment of cycling experience is primarily conducted through surveys and interviews (Gemeente Rotterdam, 2023). The perceived cycling experience is dependent on the route cyclists select for their trip. Some people may be motivated to minimise travel time, while others may prioritise cycling through safe and aesthetic environments or avoiding traffic lights (Prato, 2009). Understanding these preferences is important for designing a cycling environment that meets the needs of Rotterdam's population. This requires an analysis of route choice behaviour.

In summary, the municipality of Rotterdam is committed to encourage cycling activity as it is beneficial for health, accessibility, sustainability and liveability. Additionally, the municipality aims to guarantee a positive cycling experience. Consequently, the municipality seeks to design a cycling environment that aligns closely with the preferences of its cyclists, making cycling a safe and appealing mode of transport.

The term "cycling environment" is frequent employed throughout this research. Cycling environment includes the cycling infrastructure, for example, the presence, width, colour and type of a cycling lane, whether it is shared with a tram line, the road surface and if there are parking spaces next to the cycling lane. But also the built environment along the road, including buildings, trees, rivers, grass, parking, and other obstacles along the road, can influence cycling behaviour. The presence of other road users and their speed of driving is also a part of the cycling environment, as well as other environmental influences (e.g., weather, pollution, noise). This list, however, is not exhaustive, as numerous other factors may contribute to shaping the cycling environment and its impact on cyclists.

1.2. Insights from the literature and knowledge gaps

Extensive research has been conducted on factors that influence cycling route choice behaviour. This includes travel time, the built environment, cycling infrastructure, the natural environment, the number of intersections and turns, but also social demographics and the purpose of the trip (Zimmermann et al., 2017; Ton et al., 2017; Kaplan and Prato, 2015; Heinen et al., 2010). The majority of these studies have employed GPS data, interviews and stated preference surveys. Some studies used a stated choice experiment with generated images (Rossetti, Guevara, et al., 2018), but most studies have presented cycling environment attributes as text descriptions. Text-based representations of the cycling environment are challenging for individuals to interpret, potentially leading to invalid results (Elu et al., 2021). In contrast, using images offer a richer and more realistic way of evaluating respondent's preferences, making them an optimal choice for stated choice experiments.

In the last decade developments in computer vision and street view images have provided methodologies for understanding the effects of visual features of the environment on the way they are perceived (Rossetti, Lobel, et al., 2019; Dubey et al., 2016; Ma et al., 2021). It has been demonstrated, using real-world images, that the cycling environment significantly influences various perceptions, such as traffic safety, social safety, and beauty (Zeng et al., 2024; Ito and Biljecki, 2021; Juarez et al., 2023).

However, there is limited research on how the cycling environment influences preferences for cycling routes. Preferences are crucial as they directly inform choice behaviour, whereas perceptions alone shape impressions but do not necessarily result in choosing a specific cycling route. While a route may be perceived as beautiful and safe, if the travel time is unacceptably long, it will not be chosen. Perceptions lack these kind of trade-offs, which is necessary to analyse potential cycling environment improvements effectively. It is therefore essential to consider the preferences of individuals instead of the perceptions.

In summary, it has been determined that it is challenging to make an informed choice regarding cycling routes based solely on textual information. Additionally, studies, utilising real-world images, have identified that the cycling environment influences people's perceptions. However, there is limited research on how the cycling environment influences preferences for cycling routes. Displaying cycling environments visually can facilitate a deeper understanding of individuals' preferences regarding cycling environments in the context of cycling route choices. To the authors knowledge no studies have investigated this. By identifying these preferences, the study aims to inform the municipality of Rotterdam on effective strategies on designing cycling environments. The recently proposed model of (Cranenburgh and Garrido-Valenzuela, 2023) can accommodate choice tasks involving numerical attributes and images by integrating computer vision into a traditional discrete choice model. This model is referred to as the computer vision-enrichted discrete choice model (cv-dcm).

The cv-dcm is able to assign a predicted cycling environment utility score to each image providing a valuable measure of the perceived cycling environment. The model is not straightforward for humans to interpret, given that it is based on computer vision. So the reason behind the assignment of a specific score to a given image remains complex. It is therefore important to analyse the model using a combination of qualitative, spatial and quantitative analyses. A validity check has to be conducted to analyse whether the cv-dcm aligns with expected human decision-making in cycling route choice. Furthermore, it is valuable to analyse how different cycling environments and infrastructure characteristics affect the utility score. From the municipality's perspective, an interpretable model is particularly valuable. Explaining the factors that contribute to the utility score allows to design cycling environments that meets the preferences of cyclists.

1.3. Research Objective and research questions

The goal of this study is to explore the preferences on cycling route choice. Some people may be motivated to minimise travel time, while others may prioritise cycling through a pleasant environment or avoiding traffic lights. Additionally, the study delves deeper into the cycling environment to analyse the influence of cycling environment attributes on individuals' preferences. By identifying these preferences, the study aims to inform the municipality of Rotterdam on effective strategies on designing cycling environments that meets these preferences and to promote cycling.

The following research question will be addressed in order to accomplish this goal:

"How does the cycling environment influence cycling route choice behaviour?"

To fully answer the research question, a number of sub-questions have been formulated. The defined sub-questions are the following:

1. **SQ1 What trade-offs do individuals make regarding cycling route attributes?**

   This question addresses the trade-offs individuals make, such as travel time, traffic lights and the cycling environment, which are essential in understanding the underlying reasons behind cycling route choices.

2. **SQ2 How well does the cv-dcm align with expected human decision-making in cycling route choice?**

   This question examines the face validity of the cv-dcm that scores the cycling environment, ensuring that the model's behaviour aligns with expected human decision-making in cycling route choice. It determines which cycling environments have positive or negative influences on cycling experience.

3. **SQ3 How does the cycling environment influence the decision behaviour of the cv-dcm?**

This question is specifically focused on the role of cycling environment and infrastructure characteristics, including type, width, and colour, and how these characteristics influence the outcomes of the cv-dcm, thereby influencing the quality of the cycling experience.

4. **SQ4 How do cycling environment attributes influence cycling route choice behaviour?**

   This question identifies the impact of each cycling environment attribute on the route choice. This is particularly useful because it allows to isolate the impact of each attribute. And can thereby provide good recommendations to improve the cycling environment in Rotterdam.

5. **SQ5 How do different demographic groups (e.g., age, gender) prioritise attributes when choosing cycling routes?**

   This question provides a demographic analysis, exploring the influence of age and other factors on the trade-offs individuals make regarding cycling route choice. Some groups attach greater value to travel time, whereas other place a higher importance on the cycling environment. These groups can provide relevant information to apply tailored policies.

1.4. Scope

The city of Rotterdam is selected for this study due to its diverse population and offers opportunities for improvement in infrastructure design in certain areas (Gemeente Rotterdam, 2019b). Furthermore, the study considers most of the residential and commercial areas of Rotterdam excluding its port and surrounding areas. Figure 1.1 illustrates the area included in this research. All cycling lanes within the study area are included. In order to scope the study, the study will only focus on commuting trips, as this is the most common trip purpose (Yang et al., 2019).

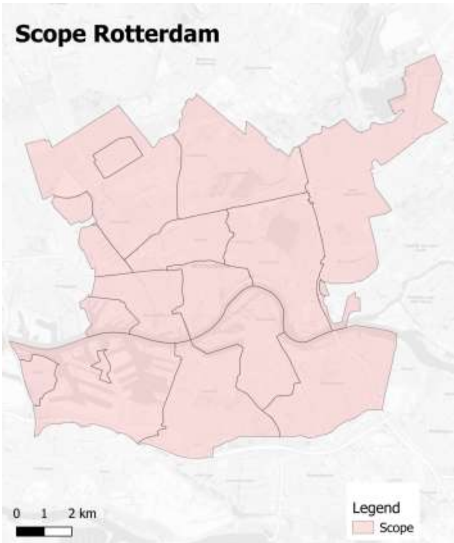


Figure 1.1: Selected area

1.5. Reading guide

The first Chapter provides an overview of the background, the identified knowledge gaps, and the main objective of this research. The main research question is identified and divided into multiple sub-questions. Chapter 2 examines the existing literature on cycling route choices and the literature concerning computer vision in combination with street view images. The section ends with identified knowledge gaps. The methodology to answer the knowledge gaps and questions is explained in Chapter 3. Chapter 4 illustrates the data collection of the street-level images, with the objective of ensuring the inclusion of all essential features and the generation of a ranking of the images. Chapter 5 outlines the setup of the stated choice experiment, which was conducted to evaluate the cycling route. Chapter 6 describes the process of collecting data on the cycling environment and matching it with the images. Chapter 7 presents the results of the stated choice experiment, including a section on the results of the cv-dcm, the cycling environment attribute model, and the latent class model. Chapter 8 offers a conclusion to the study, accompanied by a discussion of the research findings and recommendations for future work.

2

Literature review

The purpose of the literature review is to discuss what kind of research has already been done and what still needs to be investigated. The literature review discusses the current state concerning influencing factors on cycling route choices but also elaborates on computer vision methods and the use of street-level images. The final section presents a concise summary of the current state of knowledge, highlighting areas where further research is needed and suggesting potential directions for further investigation.

2.1. Factors influencing cycling route choice behaviour

The decision-making of choosing a cycling route is influenced by a number of factors. Many studies have been carried out using a stated preference approach, after which cycling route choice has been estimated using an MNL model (Rossetti, Guevara, et al., 2018; Significance, 2022). Revealed preference (RP) and stated preference (SP) are the two primary methods used in Discrete Choice Modelling (DCM) (Molin, 2024). In recent years, numerous studies have also employed a revealed preference methodology to estimate cycling route choice attributes using GPS data (Zimmermann et al., 2017; Scott et al., 2021; Dane et al., 2020; Ton et al., 2017). The advantage of SP is that it is relatively straightforward to perform, and future or non-existent routes can be included. However, a drawback is that individuals often make different choices in SC experiments compared to their real-world behaviour, potentially introducing bias (Molin, 2024). Extensive research has shown that various factors affect cycling route choice. To maintain an overview, these factors have been subdivided into trip characteristics, safety and beauty perceptions, cycling environment factors, social demographics, natural environment factors and other factors. In addition, it was investigated how these factors are expected to influence the choice of cycling routes and how they are connected to traffic safety, social safety, aesthetic appealing and effort. Table A.1 in Appendix A provides an overview of all the factors and indicating their expected influence.

2.1.1. Trip characteristics

For many individuals, the most crucial factor in cycling route choice is travel time or distance. The study by Verhoeven et al. (2018) based on GPS data in Belgium revealed that 71% percent of respondents did not diverge from the shortest possible cycling route. Another important factor to consider is the number of intersections along the route. Cyclists tend to avoid traffic lights due to the potential for long waiting time (Ton et al., 2017). The number of turns also contributes to a sense of disutility. It is often the case that cyclists will choose for the most straightforward route, which is the route with a minimal number of turns (Verhoeven et al., 2018).

2.1.2. Safety and beauty perceptions

In addition to above mentioned attribute, safety of the route is also a significant consideration (Kaplan and Prato, 2015). Two approaches to measure safety can be identified: objective safety and subjective safety. Objective safety is defined as the occurrence of cycling accidents, whereas subjective safety can be understood as perceived safety experienced by individuals (Heinen et al., 2010). Subjective safety can be further divided into two categories: traffic safety, which refers to the perceived risks of accidents, and social safety, which relates to perceived risks from threats, intimidation, or violence. Beyond safety perception, the aesthetic appeal of a route also plays a role (Zeng et al., 2024). These are perceptual latent variables which describe the way individuals process information related to a cycling route. These variables not only depend on social demographics, but also on the cycling environment of the route (Rossetti, Guevara, et al., 2018).

2.1.3. Cycling environment factors

The cycling environment is a crucial factor in determining cycling route choice behaviour. This includes not only the physical infrastructure, but also the surrounding built environment, traffic and other environmental influences.

Infrastructure design

Infrastructure features that are likely to influence cycling route choice behaviour include, for example, the presence of a cycling lane, the width of the cycling lane (Gössling and McRae, 2022), the type of cycling lane (separated or shared) (Kaplan and Prato, 2015), whether it is shared with a tram line (Kaplan and Prato, 2015), the road surface (Zimmermann et al., 2017) and if there are parking spaces next to the cycling lane (Gössling and McRae, 2022). For instance, a cycling lane may be perceived as more attractive for cycling than a street shared with cars, and a tram. These infrastructure features can influence cycling route choice to some degree. There have been several studies on this topic. The study by Kaplan and Prato (2015) who analysed cycling crashes, found that cycling lanes where cyclists are separated from other traffic are considered to create safer situations as well as greater safety perceptions among cyclists in Copenhagen. Also, the number of conflicts and amount of stress caused by road sharing is significantly reduced when cycling lanes are used (Kaplan and Prato, 2015). The study by Rossetti, Guevara, et al. (2018) analysed perceived safety using a stated choice experiment with generated images, found that perceived safety has a positive and significant influence on preferences for infrastructure design. However, the relationship between infrastructure and route choice may vary by context.

According to the study of Ton et al. (2017) that estimates cycling route choice for the inner-city of Amsterdam, based on GPS data, suggests that cyclists are insensitive to separate cycling lanes in Amsterdam. Also, the study of Bernardi et al. (2018), based on GPS data, posits that individuals are insensitive to specific cycling infrastructure, with the majority of individuals choosing the shortest route. In addition, cyclists are found to minimise travel distance and the number of intersections. The impact of distance on route choice increases in the morning peak which is characterised by a greater prevalence of home-to-work trips (Ton et al., 2017). This indicates that, despite the majority of research findings indicating a positive correlation between route choice and cycling infrastructure, this relationship appears to be context-dependent.

Built environment

Previous studies have demonstrated that several built environment factors are associated with cycling behaviour (Heinen et al., 2010; Wang et al., 2016). According to a review paper of Yang et al. (2019), there are relations with land use along the route, population density and greenery. However, the strength of these relationships is often weak or mixed, suggesting that their influence may be context-dependent. Some studies have explored how specific attributes of the built environment impact cyclists' preferences. For instance, the study of P. Chen et al. (2018) used GPS data to show that cyclists favour routes with mixed land use, trees, street lights, and urban features. Greenery, in particular, has been highlighted as a significant factor. For instance, trees creates a more aesthetically appealing route and provide cooling and shelter from the sun when temperatures are high, while also offering protection on rainy days. Nonetheless, most studies analysed built environment and cycling behaviour on a macro scale such as population density, land use mix, street connectivity, elevation or accessibility public transport. Only a few studies focused on design of the micro built environment and reported physical built environment attributes. There is inadequate knowledge which of the built environment attributes are critical for cycling behaviour.

Traffic

The presence and speed of other traffic, such as cars, trams, cyclists and pedestrians, influence cycling route choice. The findings of Misra and Watkins (2018) suggest that speed and annual average daily traffic influence the decision to choose a cycling route negatively and is different per gender. As demonstrated by **zimmermann2017bike**, traffic volume does negatively impact cycling route behaviour when it exceeds 8.000 vehicles per day. Furthermore, numerous studies have demonstrated that speed is a significant factor influencing cycling volumes. It was observed that cycling rates decreased when vehicle speeds exceeded 30 km/h, indicating that cyclists tend to avoid these routes (Jestico et al., 2016; Verhoeven et al., 2018). These findings are particularly significant in situations where cyclists are not separated from other traffic (Winters et al., 2013). On the other hand, routes through more remote areas with minimal traffic can be perceived as socially unsafe. Especially women and children would opt for alternative routes due to an unsafe feeling (Bohle, 2000).

2.1.4. Social demographics

Individuals have heterogeneous preferences regarding the cycling environment and travel time. Some people may be motivated to minimise travel time, while others may prioritise cycling through safe environments or avoiding congested roads (Prato, 2009). As (Heinen et al., 2010) posited, inexperienced cyclists, women, and elderly place a greater value on traffic safety, while others are more inclined to choose the fastest route. Female cyclists are often more likely to feel unsafe than their male counterparts under similar traffic conditions or surrounding environment (Misra and Watkins, 2018). So social demographics influence the decision-making of choosing a cycling route.

2.1.5. Natural environment factors

It is important to consider the influence of natural environment factors. The weather can have an impact, as can the time of day. In the evening, cyclists are more likely to choose a route with lighting than without, while during the day this does matter less (Vidal-Tortosa and Lovelace, 2024). According to the study Tran et al. (2020), noise and air pollution also play a role. Furthermore the terrain has influence. The presence of numerous hills necessitates greater effort, which can lead to a sense of dis-utility for cyclists (Winters et al., 2013). Rotterdam is a city with a relatively flat topography, with the exception of the bridges, which therefore does not have a significant influence.

2.1.6. Other factors

The purpose of the trip also has influence on cycling route choice behaviour. If the objective is leisure, the chosen route will likely be more aesthetically appealing, whereas if the purpose is commuting, the chosen route will be also selected based on travel time (Yang et al., 2019). Furthermore, cycling in a group or independently can also influence behaviour. Also, cycling home after a social gathering with alcohol may result in different behavioural patterns than normal.

2.1.7. Investigating cycling route choice with a SC experiment

The factors that influence the choice of cycling route have been identified. The majority of studies have employed a variety of methods, including GPS data, interviews, virtual reality experiments, and stated choice experiments with text descriptions or generated images. The use of stated choice experiments with text descriptions or generated images to investigate cycling route choice is not without limitations. Individuals find it challenging to interpret text-based cycling environments, potentially leading to less accuracy (Elu et al., 2021). Similarly, generated images may fail to capture the variability of real-world environments. In contrast, using real-world images allows for a more realistic evaluation of the cycling environment, which offers an opportunity to gain more accurate insights into route choice behaviour.

2.2. Street view images and computer vision

This section focuses on studies that have employed real-world images and computer vision to analyse the environment.

2.2.1. Street view images and computer vision general

Over the past decade, the availability of large street imagery datasets and advancements in machine learning techniques have significantly improved the scalability of methodologies for analysing how visual features influence perceptions (Ramírez et al., 2021). This progress has led to several studies that applied street-level images (SVI) and computer vision (CV) to explore relationships between visual features and perceptions such as safety, liveability, and beauty (Ma et al., 2021; Dubey et al., 2016). The study by Rossetti, Lobel, et al. (2019) employed regression models and machine learning (ML) algorithms to analyse the perception of urban space safety in Santiago, Chile. The respondents of the survey were requested to select the image that they considered to be safer. The researchers performed semantic segmentation to extract features that influence safety perceptions. Additionally, a study expanded this work by identifying demographic variables that explain the observed differences in safety perception, including gender and mobility patterns (Ramírez et al., 2021).

2.2.2. Street view images and computer vision regarding cycling

The study of Zeng et al. (2024) measured cyclists' perceptions using street-level imagery and revealed how visual features influence perceptions in terms of traffic safety, social safety, and the aesthetic appeal. Additionally, the study of Ito and Biljecki (2021) assessed a bikeability score with SVI and CV. This study demonstrated that CV techniques and SVI can be used to comprehensively assess the bikeability of cities. It suggested that micro street-level indicators (i.e. greenery or building design) may have a stronger correlation with bikeability in comparison with macro-level indicators (i.e. population density or elevation). Also cyclists' perception of the environment is analysed based on the methods virtual reality and a survey (not a stated choice experiment) (Juarez et al., 2023). It concludes that perception of street design affects commuting route choice of cyclists.

2.2.3. Computer Vision enriched Discrete Choice Modelling

In most of the above mentioned studies, respondents were requested to choose which of two images they perceived as safer, more beautiful, more bikeable or more walkable. CV techniques were then employed to identify which attributes contributed to this perception. The studies focused on how cycling environments are perceived. Perceptions alone do not account for trade-offs. In contrast, preferences provide a more direct understanding of cycling route choice behaviour, as they incorporate the balancing of various factors. To analyse preferences, other factors that influence cycling route choice as mentioned in 2.1, such as travel time, travel distance, and the number of intersections, also has to be investigated. The research of Cranenburgh and Garrido-Valenzuela (2023) proposed a new model that can handle choice tasks involving numerical attributes and images by integrating computer vision and traditional discrete choice models (cv-dcm). The study assessed residential location choice with a stated choice experiment where respondents had to choose between two locations based on the street-level conditions (the image), monthly housing cost and commuting time. This is one of the first studies that integrates images into a discrete choice model. This approach can be highly valuable for other subjects, such as safety, crowdedness and beauty, where numerical attributes alone may fail to fully capture the complexities of the choice situation. The cv-dcm can assign predicted cycling environment utility scores to images. However, since the model relies on computer vision, its decision-making process is not easily understandable to humans. As a result, the reasoning behind why a particular score is assigned to an image is complex.

2.3. Conclusion and Discussion

The first section of the literature review indicates that the selection of a cycling route is influenced by a couple of factors, including travel time, the built environment, cycling infrastructure, the natural environment, the number of intersections and turns, but also social demographics and the purpose of the trip. A significant proportion of commuter cyclists tend to favour the shortest possible route.

The development in computer vision and the availability of street view imagery have supported the increasing scalability of methodologies for analysing how visual features influence perceptions, including social safety, traffic safety, and aesthetical appeal. It was found that that attributes such as greenery, building design, and cycling infrastructure design impact the perceptions of cyclists.

Despite these studies, a significant gap remains in the current body of knowledge. Most studies that applied a stated choice experiment have presented cycling environment attributes as text descriptions.

Text-based representations of the cycling environment can be challenging for individuals to interpret, potentially leading to invalid results. Using images is more effective, as they provide a clearer representation of the environment. Studies that utilised real world images have identified that cycling environment influences people's perceptions such as how safe or aesthetic appealing an environment is. However, there is limited research on how the cycling environment influences preferences for cycling routes. Preferences are crucial as they directly inform choice behaviour, whereas perceptions alone shape impressions but do not necessarily result in choosing a specific cycling route. While a route may be perceived as beautiful and safe, if the travel time is unacceptably long, it will not be chosen. Perceptions lack these kind of trade-offs, which are necessary to evaluate potential cycling environment improvements effectively. It is therefore essential to consider the preferences of individuals instead of the perceptions.

Visualising cycling environments through images can provide valuable insights into individuals' preferences for cycling environments within the context of route choices. To the best of my knowledge, no studies have explored this approach. Such insights could be highly beneficial for informing the municipality of Rotterdam on how to design cycling environments that align with the preferences of cyclists. The recently proposed model by Cranenburgh and Garrido-Valenzuela (2023) offers a way to combine numerical attributes and images in choice tasks by incorporating computer vision into traditional discrete choice models (cv-dcm). However, since the model relies on computer vision, its decision-making process is not easily understandable to humans. To address this, it is also valuable to examine the model through a combination of qualitative, spatial, and quantitative analyses.

3 Methodology

This chapter outlines the methodology to achieve the research objective. Initially, the framework of the research methodology is presented, and subsequently, the various methods are explained in greater detail.

3.1. Framework of research methodology

The goal of this study is to explore cycling route preferences and to analyse the influence of cycling environment attributes on cycling route choice. This will be done to develop an advise regarding the design of cycling-friendly environments and the promotion of cycling activity. Achieving this goal requires a methodology. This begins with the research and data collection phase, where the necessary research and data are gathered for conducting the stated choice experiment. The influence of the attributes will be estimated by applying the cv-dcm model, a latent class model and a cycling environment attributes model. The results of all the models are then analysed. Consequently, the evaluation results in a comprehensive understanding of cycling route choice behaviour and influencing factors of the cycling environment on cycling route choice. This results forms the basis for deriving insightful conclusions and offering well-informed recommendations about cycling route preferences to policy makers.

The methodological framework is presented in Figure 3.1. This approach serves to provide the reader with a clear understanding of the purpose of the analysis that will be conducted in each section. Blocks in the results section correspond to the sub questions, which are highlighted with green text positioned in the upper-left corner. Each of the grey blocks represents chapters within this study. This approach serves to provide the reader with a clear understanding of the purpose of the analysis conducted in each section.

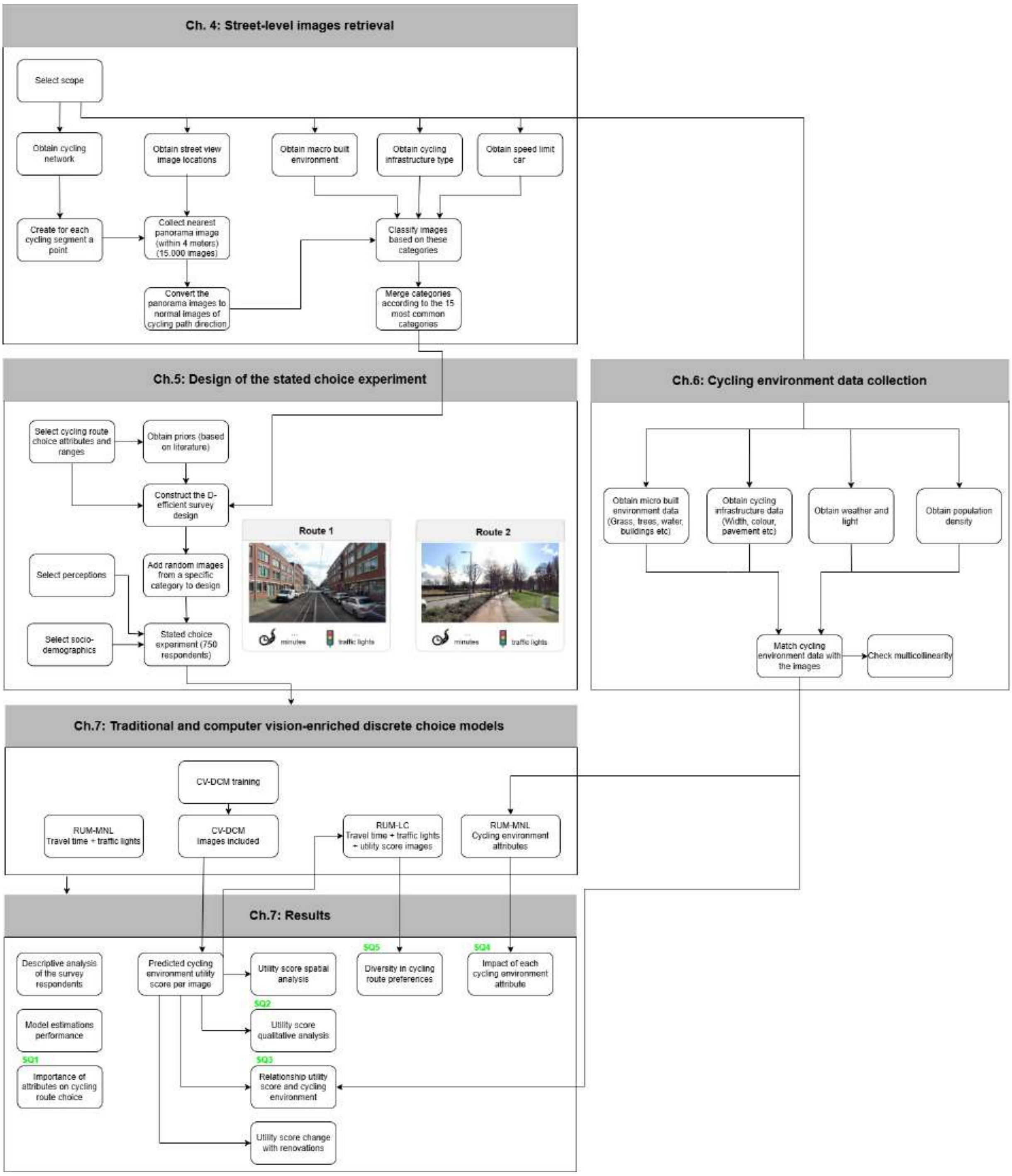


Figure 3.1: Methodological framework

3.2. Street-level image retrieval

Street-level images are applied to determine the visual cycling environment for the stated choice model. The methodology for the construction of the image database is partly adopted from the approach of Cranenburgh and Garrido-Valenzuela (2023) regarding residential location choice. Chapter 4.2 gives an extensively explanation how the street-level images are collected and analysed.

3.3. Stated choice experiment (SC)

To design a cycling environment that aligns closely with the preferences of cyclists it is essential to understand their choices when selecting routes. A stated choice experiment determines the independent influence of different variables on observed outcomes (Rose and Bliemer, 2009). The variables are derived from literature research and brainstorm sessions with the municipality and university supervisors. The manner in which the attributes, ranges and underlying design were created is described in Chapter 5.

In order to recruit individuals willing to complete the survey, the panel data company Cint was asked to conduct the recruitment of respondents. The respondents will be financially compensated for their participation in the survey. In order to analyse how different subgroups within the population make decisions regarding cycling routes, it is of great importance that the sample is representative of the Dutch population. To ensure this, data will be filtered in advance based on gender, age, and region through the data of CBS (CBS, 2024a).

3.4. Discrete choice models (DCM)

A computer vision-enriched discrete choice modelling (cv-dcm) method will be employed to predict cycling route choice. Initially, the conventional random utility maximisation-multinomial logit discrete choice model (RUM-MNL DCM) will be explained, after which the added value of a Latent Class (LC) choice model will be discussed. Section 3.5 describes the computer vision component.

Discrete choice models are used to explain and predict a choice from a set of two or more discrete alternatives (Sifringer et al., 2020). It has been applied as a mathematical tool to model route choices for more than forty years. It considers an economic and quantitative approach with the assumption that each choice made is the outcome of a rational choice process (Columbiauniversity, 2020).

Daniel McFadden developed the well-known Random Utility Maximisation (RUM) Model. This model assumes that the decision-maker will choose the alternative that maximises their utility (McFadden, 1974). The utility of an alternative is comprised of the observed- and the unobserved utility. The observed utility is based on observed attributes that are expected to impact the decision. The unobserved utility is based on everything else that governs the individual's choice. This utility is randomly distributed across all individual choices, contributing to the stochastic nature of discrete choice models. Equation 3.1 shows the equation for utility U for alternative i.

The objective of the maximum likelihood estimation is to identify the beta parameters that make the data most likely, thereby determining the beta parameters that maximise the log likelihood (LL) function. The model will estimate the weight of all these observed attributes. The standard equation of the linear-additive RUM model is shown in equation 3.2. Based on these weights, it is possible to calculate the probability that a respondent will choose a certain alternative. This can be done with the multinomial logit model (MNL). In MNL models, the error terms are independently and identically Extreme Value Type I distributed (i.i.d.) with variance $\frac{\pi^2}{6}$. Equation 3.3 shows the form of the linear-additive MNL model.

$$U_i = V_i + \varepsilon_i \tag{3.1}$$

$$U_i = \sum_m \beta_m \cdot x_{im} + \varepsilon_{in} \tag{3.2}$$

$$P_{in} = \frac{e^{V_{in}}}{\sum_j e^{V_{jn}}} \tag{3.3}$$

3.4.1. Latent class models (LC)

However the RUM-MNL model has been criticised on a couple of components. First, an important observation about traditional MNL model is that the model does not distinguish between individuals. In reality, individuals have different preferences (Mouter et al., 2017). So the one-size-fits-all imposed by traditional Multinomial Logit (MNL) choice models is a simple way to model behaviour. Therefore a latent class (LC) choice model can be applied to identify different subgroups within populations that are similar based on observed characteristics (Weller et al., 2020). Which means that LC models are able to account for heterogeneity across different segments in the population. By accounting for this groups the LC choice model often provides a better fit to the data compared to the traditional RUM-MNL models. This leads to more reliable estimates of parameters and predictions of choice probabilities. From a more practical perspective, the classes revealed by the LC model can provide relevant information to specifically target various groups by applying tailored policies which aligns with the municipality's desired outcome. Formula 3.4 shows the formula of the latent class model.

$$P_n(i|\beta) = \sum_{s=1}^{S} \pi_{ns} P_n(i|\beta_s) \tag{3.4}$$

3.5. Computer Vision enriched Discrete Choice Modelling (cv-dcm)

Images offer an additional source of data for explaining choice behaviour. In many choice situations it is hard to make a choice without visual information. For example in residential location choice (Cranenburgh and Garrido-Valenzuela, 2023), cycling route choice and tourist destination choice (Pan et al., 2021). Recently, Cranenburgh and Garrido-Valenzuela (2023) have proposed a new class of discrete choice models –called Computer Vision-enriched Discrete Choice Models (cv-dcms). This new method regarding residential location choice will be applied in this research. An extensive explanation of the computer vision part of this method can be found in their research. A summary of the methodology will be provided in this section.

CV is a crucial technology for extracting information from visual data. In this research CV will be used to convert images into data that can be applied to contribute in the DCM. CV models are designed to detect scenes and objects incorporating over one billion weights in the largest models. Images are composed of pixels, whereby each pixel contains three colour channels, namely red, green and blue (RGB) and a location, namely height and width (h x w). The images are represented as three dimension tensors, which are multi-dimensional arrays of numerical values. These tensors facilitate efficient image processing, with the three dimensions corresponding to width, height, and colour channels. A typical image contains millions of pixels. However, directly using pixel in a CV model is not efficient due to the amount of data and the limited information that individual pixels have. Therefore the CV model to be applied consists of a feature extractor and a classifier. The feature extractor generally is a deep neural network and is responsible for extracting relevant features of the images. It comprises a relatively modest 86 million weights. The output of the feature extractor is the feature map which is a flat array of floating points with a size of 1 x 1000. So the feature map is comprised of most of the information that can be seen in the image and is readable for the computer, while also being of an appropriate scale. The working of the CV model is displayed in Figure 3.2. The pre-trained feature extractor from the DeiT base model will be applied (Data-efficient image Transformer). DeiT models are vision transformer-based architectures known for their data efficiency, achieving competitive performance on benchmark datasets like ImageNet (ImageNet, 2024) while requiring less computational power and data than many other models (Touvron et al., 2021).

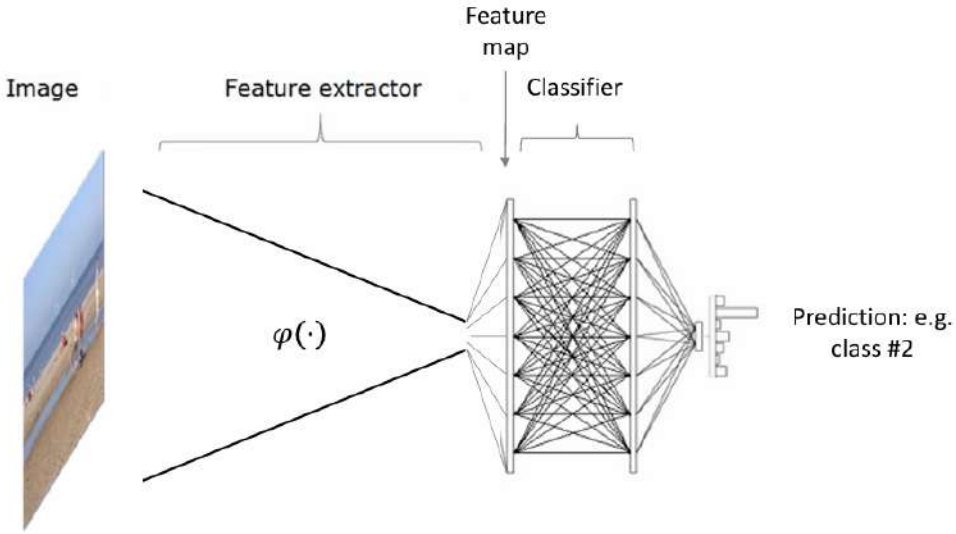


Figure 3.2: Feature extraction and classification.
Adopted from Cranenburgh and Garrido-Valenzuela, 2023

The image represented by the feature map is applied in conjunction with the numerical attributes in the utility function. Subsequently, the probability that a respondent will choose a certain alternative can be estimated. This is achieved through the use of a Multilayer Perceptron (MLP), a type of a deep neural network, which functions in a manner identical to that of a standard DCM. Equation 3.5 illustrates the derivation of utility, whereby the first part denotes the utility associated with the numerical attributes, the second part denotes the utility associated with the image, and the third part denotes the error term. Figure 3.3 shows the model structure of the cv-dcm.

$$U_i = \underbrace{\sum_m \beta_m \cdot x_{im}}_{\text{Utility derived from numerical attributes}} + \underbrace{\sum_k \beta_k \cdot z_{ik}}_{\text{Utility derived from image feature map}} + \varepsilon_{in} \tag{3.5}$$

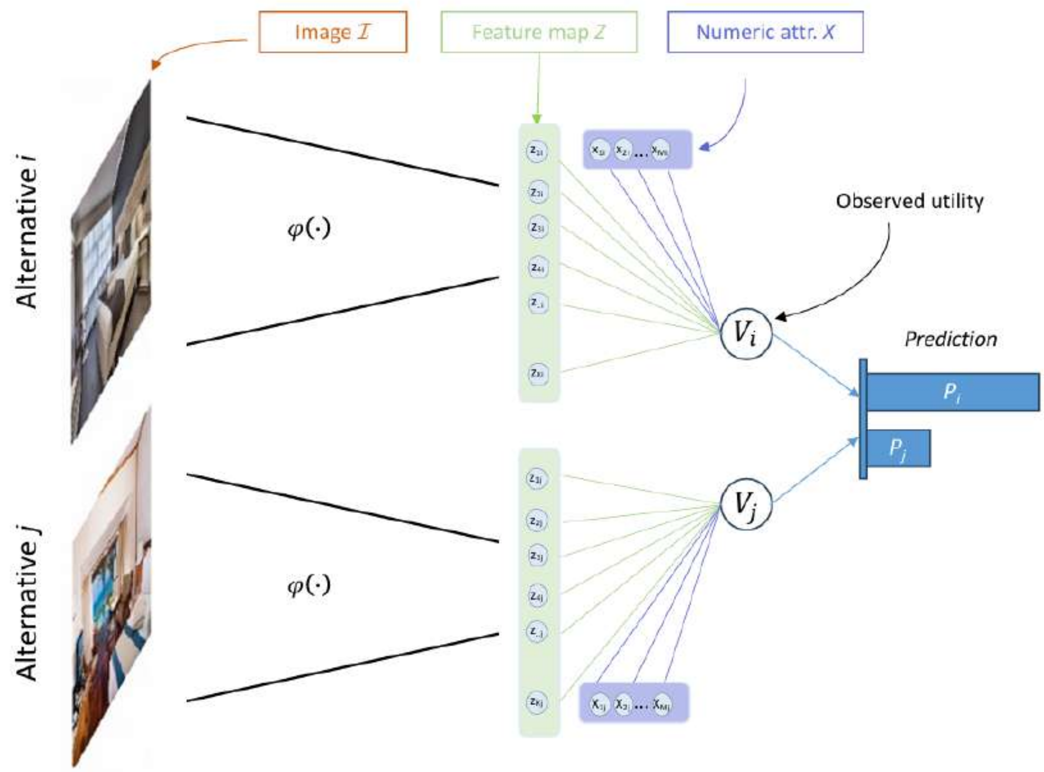


Figure 3.3: Model structure of the cv-dcm.
Adopted from Cranenburgh and Garrido-Valenzuela, 2023

4 Street-level image retrieval

Street-level images are applied to determine the visual cycling environment of cycling roads for the stated choice model. Each cycling lane requires a street-level image of the surrounding area. The municipality of Rotterdam has a database of street level images with a total of more than 600,000 images, also with images on the cycling lane (Cyclomedia, 2023). The location and direction of each image is recorded. Images are automatically taken at intervals (every 10 to 20 metres). Each image captures the entire area around the recording position.

4.1. Image collection

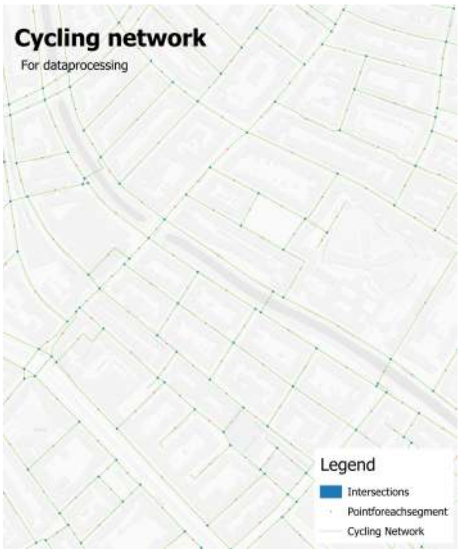
In addition to the street level images, the entire cycling network within the scope is included. This encompasses all roads where cycling is suitable. The cycling network data applied for this study is from Fietsersbond (2020). First the public data from OpenStreetMap (2024) was explored, yet the data from the Fietsersbond is more complete. The data also shows the type of cycle path, the pavement type, the maximum speed of cars and the average speed of cyclists. While this data is also available in Open Street Map, it is often incomplete. The cycling network is generated within the geographic information system (GIS) environment (QGIS, 2023). Figure 4.1a displays the complete network of cycling lanes within the scope. Figure 4.2b displays the distribution of street-level images across the city. It was observed that images are captured on nearly every road.

(a) Cycling network

(b) Street-level images

Figure 4.1: Cycling network and street-level images
Adapted from Fietsersbond, 2020 & Cyclomedia, 2023 and created with QGIS, 2023.

The Fietsersbond cycling network is constructed of segments, which are defined as stretches of cycling path that begin at an intersection and end at another intersection. Segments larger than three metres are included in the network, as segments smaller than this size are often intersections. Subsequently for each segment, a point is created in the middle of the segment, resulting in a grid of points as visualised in Figure 4.2a. Then, the nearest street-level image for each point on the grid is retrieved. In the absence of an image within a four-metre radius of a given point, no image is included. This approach is applied to avoid the retrieval of images from locations unsuitable for cycling. Figure 4.2 illustrates the methodology applied to obtain a good first selection of street level images linked to the cycling network within the scope. It can be observed that the location of the image and the representation of the cycling network aligns with the actual geographical context. In total, approximately 13,000 images were captured.

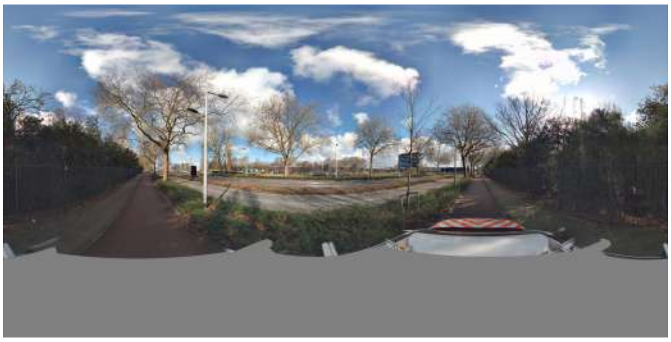


(a) Grid of points for segments and intersections (Rotterdam Noord)

(b) Retrieve the nearest street-level image (Rotterdam Noord)

Figure 4.2: Street-level image collection per segment
Adapted from Fietsersbond, 2020 & Cyclomedia, 2023 and created with QGIS, 2023.

The images are 360-degree panorama photos, which has to be converted into 90-degree images of the cycling path direction. Only this direction is of interest, as it is aimed to view the front view of the cycling path and not the side view or the back view. This is done based on the direction of the cycling lane and given that the centre of the panorama image is always oriented towards the north. Figure 4.3a shows an example of a panorama street-level image and figure 4.3b shows an example of an street-level image that can be included in the survey.



(a) Example of a panorama street-level image

(b) Example of a street-level image for in the survey

Figure 4.3: From panorama 360-degree image to a normal 90-degree image

4.2. Analysis of the images

All characteristics that influence cycling environment scores has to be visible in the images for the survey. For instance, if no images of cycling lanes in an industrial area are included in the survey, the model will be unable to assess these images effectively. To ensure that all characteristics are included it is important to examine all different types of cycling paths and environments.

Section 5 provides a detailed explanation about the stated choice experiment. For now it is important that knowledge about attribute levels is crucial for the construction of the survey. However images lack attribute levels. This issue is addressed by analysing images based on the cycling path and their environment. On this way, a ranking of the images is established. This information will then be utilised to determine which images will be selected for comparison.

A review of the literature reveals that the choice of cycling route is frequently influenced by the type of cycling lane (Gössling and McRae, 2022; Kaplan and Prato, 2015; Zimmermann et al., 2017). It was thus decided that images have to be distinguished on this basis. Additionally studies have demonstrated that there is a relationship between several built environment features and cycling behaviour (Heinen et al., 2010; Wang et al., 2016). However these relations were often weak or mixed as stated in Yang et al. (2019). Findings of Misra and Watkins (2018) revealed that traffic characteristics such as speed and the amount of traffic influence the decision to choose a cycling route. Based on literature review and data available the decision was taken to classify the images based on the cycling infrastructure, built environment and speed of the car.

The data from Fietsersbond (2020), which was used to create the cycle network, also indicates the type of cycle path. The data from the municipality's urban management department was applied to determine the built environment. The data from Rijkswaterstaat (2024) was used to determine the speed limit of each road. These datasets were linked with the cycling network. The dataset originally consisted of several categories, but for clarity and to avoid an excessively large number of categories, many were subsequently merged. Table 4.1 shows the attributes and their corresponding attribute level.

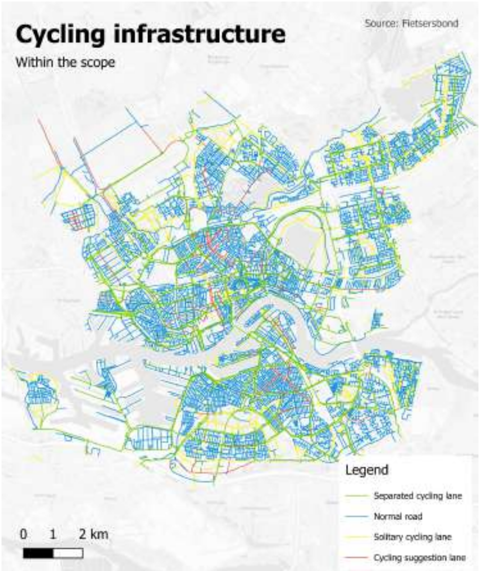
Attribute	Attribute Levels
Cycling infrastructure	Solitary cycling lane Separated cycling lane Normal road Cycling suggestion lane
Built environment	Recreational area Residential area Neighbourhood access Main road Industrial area
Maximum speed car	Not applicable 30 km/h 50 km/h

Table 4.1: Attributes and their corresponding attribute levels

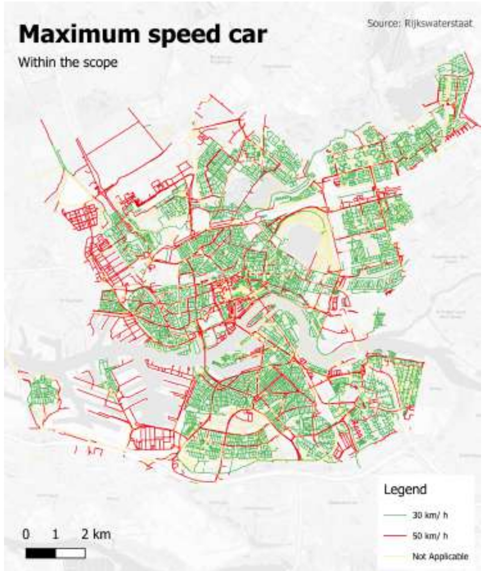
Cycling infrastructure is classified into four categories. A solitary cycling lane is defined as a lane exclusively for cyclists, with the absence of car road nearby. On the other hand, a separated cycling lane is situated alongside a car road. A normal road is characterised by the absence of a dedicated cycling lane. A cycling suggestion lane is a lane adjacent to a car lane, marked by a painted line and often painted surface.

Built environment is classified into five categories. Recreational areas are defined as natural areas, for example De Kralingse Plas in Rotterdam. Residential areas are defined as areas where people live. A neighbourhood access road is defined as a road with a residential function that nevertheless has to accommodate a considerable volume of traffic. A main road is defined as a road with a connecting function between areas that can handle high traffic volumes. Industrial areas are designated for industrial activities.

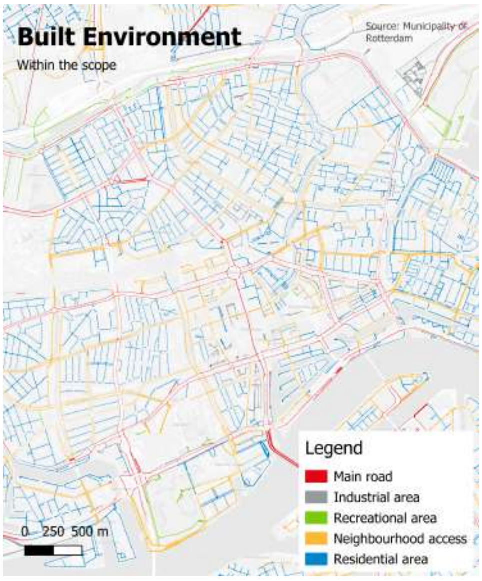
The maximum speed of the car is classified into three categories. Maximum speed car does not apply to the designated cycling lanes, where no cars are permitted, so this is covered by ’Not applicable’. Roads with a maximum speed of 30 km/h or less are designated as ”30 km/ h”. Roads with a maximum speed of 50 km/h or higher are designated as ”50 km/h.” It was analysed that there is a limited number of roads with a maximum speed higher than 50 km/h. Figures 4.4 visualise the cycling infrastructure, maximum speed of car and the built environment. At first glance it is notable that there are many normal roads in a residential area with a max speed of 30 km/ h.



(a) Cycling infrastructure



(b) Maximum speed of the car



(c) Built environment

Figure 4.4: Images are classified into categories based on these three attributes
Adapted from Fietsersbond, 2020 & Rijkswaterstaat, 2024 and created with QGIS, 2023.

All images are sorted according to cycling infrastructure, built environment and maximum speed of the car. An exhaustive analysis of the images revealed that sometimes, motorways, bridges, pedestrian areas and parking areas were captured. As motorways and pedestrian areas are not intended for cycling, these were excluded. Further, the survey indicates that the image is representative of the entire route. It is impractical to cycle the entire route over parking areas or bridges, and thus these have also been excluded.

Additionally not all combinations are applicable. For instance, when a cycle lane is either a solitary cycling lane or a separated cycling lane, the maximum speed is not applicable, given that no cars are permitted on a cycle lane. The same can be said for normal road and cycling suggestion lanes, where the maximum speed is either 30 km/h or 50 km/h.

Furthermore there are a lot of combinations that do not commonly occur. For example, a cycling suggestion lane in a recreational area with a speed limit of 50 km/h is not common in Rotterdam. The same can be said for a solitary cycling lane in an industrial area and many others.

The decision was taken to categorise the images according to the 15 most common categories. Categories with few images have been merged with a category that is very similar. For instance, the category with images of a separated cycling lane in a recreational area was merged with the category with images of a solitary cycling lane in a recreational area. This approach was taken to ensure that each category contained more than 150 images. This was deemed necessary to prevent the same images from a less common category from appearing multiple times in the survey. For example, an image of a solitary cycling lane in an industrial area. In reality, such categories rarely occur. Table 4.2 displays the 15 categories and the the corresponding number of images and appendix B visualises collages of these categories. This applied methodology guarantees the inclusion of all essential features and enables the establishment of a ranking of the images.

No.	Cycling infrastructure	Max speed car	Built Environment	Image count	Appendix
1	Normal road	30	Residential	7262	B.1i
2	Normal road	30	Access road	1070	B.1j
3	Separated cycling lane	N/A	Main road	681	B.1f
4	Separated cycling lane	N/A	Access road	623	B.1e
5	Normal road	50	Access road	475	B.1n
6	Normal road	50	Industrial	433	B.1o
7	Solitary cycling lane	N/A	Residential	427	B.1b
8	Cycling suggestion lane	50	Access road	383	B.1h
9	Normal road	50	Residential	238	B.1m
10	Solitary cycling lane	N/A	Recreational	233	B.1a
11	Normal road	30	Main road	201	B.1k
12	Separated cycling lane	N/A	Residential	185	B.1d
13	Cycling suggestion lane	30	Access road	169	B.1g
14	Normal road	30	Industrial	166	B.1l
15	Solitary cycling lane	N/A	Main road	149	B.1c

Table 4.2: The final 15 categories and their image count

5
Design of the stated choice experiment

This chapter describes the set up of the cycling route stated choice experiment. The aim of the survey is to investigate the impact of the cycling environment on cycling route choice. And to determine what trade-offs individuals make between the cycling environment and other route characteristics. This is achieved through a survey which asks people to chose their preferred route based on an image of the route and other route characteristics.

The set up of the stated choice experiment is based on the book 'Environmental Valuation with Discrete Choice Experiments' (Mariel et al., 2021). The process of creating the survey presents a number of challenges. A main challenge of SC experiments is to construct choice situations that resemble real world decisions. This necessitates an investigation and analysis of the attributes and ranges in question. Another challenge of SC experiments is to create sufficient variation in the choice situations in order that the intended utility functions can be estimated in such a way that estimated parameters are reliable and thus have small standard errors. This can be achieved by selecting an appropriate experimental design (Molin, 2024). In addition, it is important to ensure that the selected tasks do not overwhelm or exhaust the respondents.

5.1. Attribute selection

In order to determine the attributes, it is essential to include attributes that are most important for individuals. Further, it is also essential to include attributes that can be influenced by policy and design (Molin, 2024). First the attributes have to be determined. This is derived from literature research and brainstorm sessions.

The study of Verhoeven et al. (2018) revealed that 71% of the respondents did not differ from the shortest possible cycling route. Also the studies of Ton et al. (2017) and Bernardi et al. (2018) stated that the majority of individuals choose the shortest route. So literature research revealed that travel time is the most significant factor influencing cycling route choice. Another important factor to consider is the number of intersections along the route (Ton et al., 2017). Cyclist tend to avoid traffic lights due to the dislike of waiting time. The number of turns also contributes to a sense of disutility. It is often the case that cyclist will choose for the most straightforward route (Verhoeven et al., 2018).

The cycling environment also has an influence on the choice of cycling route, as described in section 2.1.3. The cycling environment includes factors such as the design of the cycling infrastructure, the built environment, and the presence and speed of other traffic, all illustrated in the image. Further, the natural environment, including weather and time of day, has an impact. As illustrated in the images, the images were made during daylight hours, not in the evening and were made in cloudy or sunny weather, not in rainfall.

Furthermore, the influence of subjective perceptions, such as beauty, traffic safety and social safety, on cycling behaviour will be examined. The research of Zeng et al. (2024) and Rossetti, Guevara, et al. (2018) demonstrates that perceptions frequently have an influence on cycling behaviour. These three perceptions are not directly quantifiable; not something that the model can directly extract from the image. Therefore, after the stated choice experiment, respondents are asked to rate a number of images they have seen in the stated choice experiment on traffic safety, social safety and beauty.

As explained in Section 2.1.4, individuals have heterogeneous preferences regarding cycling route choice. Therefore also social demographic information and questions about cycling are asked such as age, gender and experience (Heinen et al., 2010; Misra and Watkins, 2018). Moreover, the municipality has standard demographic data questions, which has been incorporated into the survey.

Based on the attributes identified through literature research and the insights gained from the Lectures of (Molin, 2024), several survey designs were created. To determine a final optimal survey design, a small case study was conducted. The two routes I typically take from my house to the railway station were analysed and incorporated into a survey. The various survey designs can be found in Appendix C Subsequently, the surveys were tested on experts and presented to my supervisors from TU Delft and the municipality. From this, some conclusions were derived.

- Including all of the aforementioned attributes would be too overwhelming for respondents.
- The survey designs were created with one image and with multiple images in a route. Including multiple images per route resembles real world decisions better. However, this approach may also result in respondents feeling overwhelmed and uncertain about which images to focus on.
- In some survey designs, the speed and intensity of cars are considered as attribute. Given that car speed and intensity can also be derived from the image, it is unnecessary and can be sometimes contradictory to include as a separate attribute. For instance when car intensity is described as high, but no cars are visible in the image, the survey will be contradictory.
- It is beneficial to include attributes that can be influenced by policy and design. Changing the number of turns is challenging, as it would necessitate a comprehensive redesign of the city district's layout. In contrast, number of traffic lights can be more easily influenced by the municipality.

Based on the input of experts and brainstorming sessions with my supervisors, the final attributes for the survey were determined. These are the image of the route, the travel time and the number of traffic lights.

5.2. Attribute level selection

The range and level has to be defined for these three attributes. Initially images lack the attribute levels necessary for the implementation of an experimental design. This issue is addressed in Section 4.2 where the location of the image is analysed (based on cycling infrastructure, the built environment and maximum speed of cars) to enable the incorporation of image attribute levels. The images are categorised according to the 15 most common categories.

The research of (Rose and Bliemer, 2009) says that applying a wide range (e.g. 5 min - 10 min) is statistically preferable than applying a narrow range (e.g. 5 min - 6 min) as this will theoretically lead to better parameter estimates with a smaller standard error. Although applying a too wide range may also be problematic as it will likely result in choice tasks with dominated alternatives. As stated in (Ton et al., 2017) and many other investigations cyclists prioritise travel time, aiming for the quickest route to their destination. Therefore, it can be concluded that travel time is a very dominant attribute in the context of cycling route choice behaviour. When a wide range of travel times is applied, it is likely that the dominant alternative with the shortest travel time will be chosen.

Given that the images are categorised into 15 categories, it is recommended that 3, 5, or 15 levels for traffic lights and travel time be selected to ensure attribute balance. Additionally, a travel time of approximately 10 minutes was selected. This duration represents a typical and realistic cycling trip length for commuting or short-distance trips in urban settings such as Rotterdam. In a design, it is beneficial to be able to compare all levels, including the lowest and highest levels, in a way that does not create dominant alternatives (Walker et al., 2018). Consequently, a range of travel times of three minutes with three levels was selected. It is expected that non-linear effects can be observed, therefore, more than two levels are required so non-linearities can be estimated in further research. The range for travel time are defined as 8 min, 11 min and 14 min.

The number of levels for traffic lights has been selected to align with that of travel time, namely three. Sometimes in images traffic lights can be seen. Consequently, if zero is designated as the range for traffic lights, the choice task may appear contradictory. Therefore, range for traffic lights are defined as 1, 2, 3.

5.3. Survey layout

Respondents are asked to compare two different cycling routes and to choose the one they would cycle. When replying to each question, they had to consider the following:

- Imagine you are cycling from your work, train station, school, or daily activity to your home.
- There are two cycling routes you can take.
- The routes differ only in **travel time**, the number of **traffic lights**, and the **cycling environment** shown in the photo.
- In all other aspects, such as the weather, the cycling routes are the same.
- **Which route would you choose?**
- You can assume the following:
  - You are cycling alone.
  - You are not in a hurry.
  - The photo gives a good idea of what the **entire route** looks like.
  - The travel time is the **total time** for the route, **including waiting at traffic lights.**
  - The weather is partly cloudy with no rain.

Figure 5.1 provides an example of a visual representation of the survey layout.

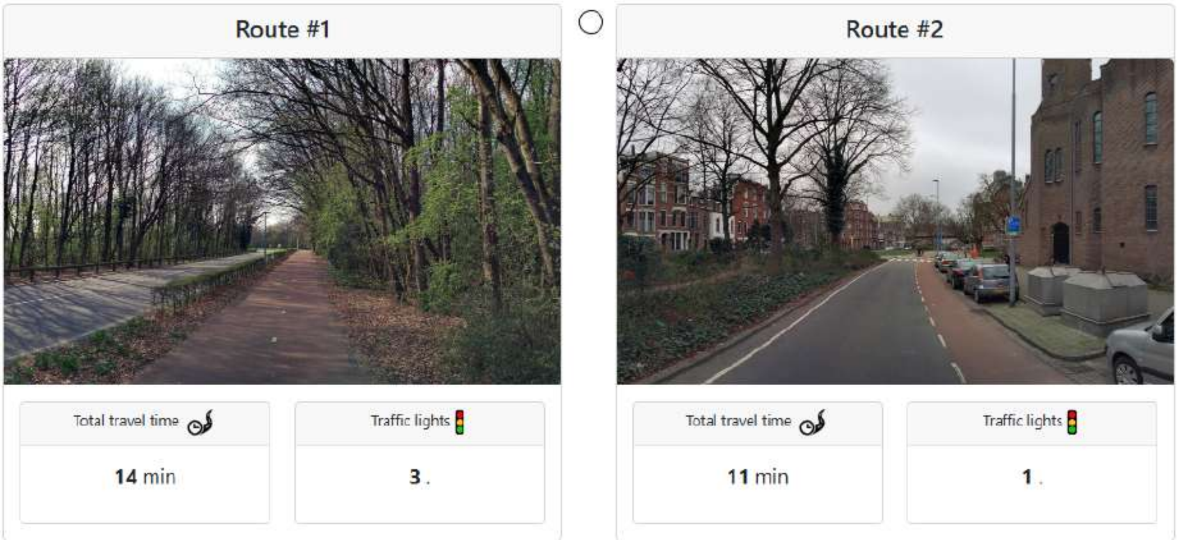


Figure 5.1: Example of a choice situation Part I

5.4. Efficient design

For any SC study, there exist many experimental designs that could be constructed. The design types that are considered are a full factorial design, a random fractional factorial design, an orthogonal design and an efficient design.

The number of choice situations that has to be generated in the full factorial design for this research is too large. Therefore a random fractional factorial design can be considered, whereby random choice situations from the full factorial design are selected. It is evident that there are more optimal and structured methods for creating a design that will result in more reliable parameters. So another design to be considered is the orthogonal design, which aims to minimise the correlation between the attribute levels in the choice situations (Rose and Bliemer, 2009). This results in lower standard errors and consequently reliable parameters. However, in an orthogonal design, dominant alternatives exist, which reveal no information about trade-offs and should therefore be avoided. If these choice situations are removed correlations between attribute levels will be introduced which makes the design less efficient (Molin, 2024). A type of design where dominant alternatives are excluded is the efficient design. The objective of this design is to achieve a balance between the utilities of the alternatives in the choice situations. This approach allows for the maximisation of information about trade-offs and the minimisation of the standard error of the parameters. In order to construct an efficient design, it is necessary to obtain priors that balance the utilities of the choice alternatives. These priors can be derived from literature research or a small pilot study. The use of inaccurate priors will result in less efficient and biased parameters. Furthermore, when dominance is a significant issue, an efficient design is proved to be more efficient.

For this study an efficient design has been selected, given that travel time represents a dominant factor in this study and that there is existing literature on cycling route choice behaviour in the Netherlands, which provides valuable insights and prior knowledge. The priors are obtained from the study of (Significance, 2022).

The study of (Significance, 2022) determines the travel time multipliers for cycling path comfort levels. The experiment was presented as a route choice experiment, with two route alternatives (Trip A, Trip B), each described by five attributes: travel time, cycling path configuration, pavement type, amount of bypassing car and beauty of the route. The parameters of the cycling path configuration, which encompass both the infrastructure and the maximum speed, are considered in order to determine the image category parameters. The beauty of a route reflect the characteristics of the built environment to a degree. For example, an industrial area is unlikely to be perceived as beautiful, whereas a recreational area is more likely to be perceived as such. However, these parameters were found to be relatively high, and there is a distinction between the concepts of beauty and the built environment. Additionally, the literature revealed that the relationship between the built environment and cycling behaviour is often complex and not always straightforward. Therefore, the value of built environment parameters is reduced to a smaller range. Traffic lights were not included in this study. Assuming that people dislike waiting time more than travel time, it was concluded that the beta parameter of traffic lights have to be a negative sign.

Furthermore, the study used the multiplicative formulation, while in this study the additive (dummy) formulation will be used as described in section 3.4. So the parameter estimates has to be converted to the additive formulation. The final parameters are displayed in Table 5.1. With these parameters an efficient design is created in Ngene. Thirty choice situations are required as we want to maintain attribute balance and the number of choice situations has to be higher than number of estimated parameters. Ngene is a software that allows to create and analyse stated choice experimental designs (ChoiceMetrics, 2024). The manual of Ngene is consulted to create a syntax code as can be seen in Appendix D.1. The efficient design with the lowest D-error after fifteen minutes was selected for the pilot survey. Appendix D.2 shows the efficient design.

Parameter	Beta Value	Cycling infrastructure	Speed Limit	Built Environment
b_time	-0.2707			
b_trafficlights	-0.1330			
b_img.dummy[0]	-1.002	Normal road	50	Access road
b_img.dummy[1]	-0.921	Normal road	50	Industrial
b_img.dummy[2]	-0.850	Normal road	50	Residential
b_img.dummy[3]	-0.720	Cycling suggestion lane	50	Access road
b_img.dummy[4]	-0.663	Normal road	30	Industrial
b_img.dummy[5]	-0.582	Normal road	30	Main road
b_img.dummy[6]	-0.512	Normal road	30	Access road
b_img.dummy[7]	-0.471	Cycling suggestion lane	30	Access road
b_img.dummy[8]	-0.466	Normal road	30	Residential
b_img.dummy[9]	-0.390	Separated cycling lane	N/A	Main road
b_img.dummy[10]	-0.319	Separated cycling lane	N/A	Access road
b_img.dummy[11]	-0.273	Separated cycling lane	N/A	Residential
b_img.dummy[12]	-0.116	Solitary cycling lane	N/A	Main road
b_img.dummy[13]	-0.046	Solitary cycling lane	N/A	Residential
b_img.dummy[14]	0	Solitary cycling lane	N/A	Recreational

Table 5.1: Prior beta parameters

5.5. Survey design and implementation

After the generation of the efficient design, a random selection of images from a specific category has been incorporated into the design. To illustrate, if alt1.image is 14, a random image from the category of a solitary cycling lane in a recreational area has been included. Table 5.1 also provides a reference which category belongs to which number.

In order to prevent the machine learning model from over-fitting the data, it is necessary to split the data set into a training set and a test set (Muraina, 2022). Firstly, each respondent is randomly assigned among these sets, comprising 80% and 20% of the total respectively. Secondly, the image category is randomly assigned among these sets. Respondents from the training set will only see images from the training set, and vice versa. The train set is used for training the model; the test is unknown to the model during training and is used to evaluate the performance of the model. If the trained model overfits the data, a difference in performance between the training and testing sets will be seen (Cranenburgh and Garrido-Valenzuela, 2023).

As previously indicated the efficient design comprises thirty choice situations, which is done to maintain attribute balance. However, it is unreasonable to expect respondents to engage in thirty choice situations. After a certain point, respondents will become disinterested. Therefore, it is necessary to divide the tasks into fifteen choice situations per respondent. Hence, two design blocks are created. Firstly, the design block number (1 or 2) was randomly assigned to each respondent. Secondly, the order of the choice questions was randomised for each respondent. Thirdly, the order of the left/right alternatives as defined in the underlying design was randomised within and between respondents. Lastly, it was guaranteed that respondents would not see the same image more than once during the first part of of the survey.

In collaboration with PhD'er Francisco Garrido-Valenzuela (Garrido-Valenzuela, 2024) a website was developed for the survey using Python Dash (Plotly, 2024). The survey consists of three parts: 1) fifteen choice situations, in which participants have to select their preferred route for each; 2) five image rating questions, based on images seen previously on traffic safety, social safety and beauty; and 3) socio-demographic information and questions about cycling. The survey can be seen in Appendix E. The link to the survey is: http://cycling-route-survey.tbm.tudelft.nl/.

6 Cycling environment data collection

As previously stated in Chapter 4.2, the images were categorised according to three different variables: cycling infrastructure, built environment and speed of traffic. This was done to include the full range of cycling environment characteristics. However, to answer the research question regarding the influence of the cycling environment on cycling route choice behaviour, it is necessary to collect further information about the environment shown in the images. This information can be used to interpret the cv-dcm and to develop a model that will examine the impact of different infrastructure elements and built environment characteristics on cycling route choice.

6.1. Cycling environment factors

In the literature review, which can be found in Chapter 2.1.3, an investigation was conducted into the environmental factors that influence the decision-making process when selecting a cycling route. Infrastructure characteristics that are likely to influence cycling route choice behaviour include for example the presence of a cycling lane, the width of the cycling lane (Gössling and McRae, 2022), the type of cycling lane (segregated or shared) (Kaplan and Prato, 2015), whether it is shared with a tram line (Kaplan and Prato, 2015), the road surface (Zimmermann et al., 2017) and if there are parking spaces next to the cycling lane (Gössling and McRae, 2022). Additionally, previous studies of the relationship between the built environment and cycling have demonstrated that several built environment factors are associated with cycling behaviour (Heinen et al., 2010; Wang et al., 2016). According to the review paper of (Yang et al., 2019) there are relations with the amount and type of buildings, greenery, water, public facilities and population density. Furthermore, the presence and speed of other traffic, such as cars, trams, cyclists, e-bikes, cargo bikes, and pedestrians, influence cycling route choice (Misra and Watkins, 2018). Additionally, it is important to consider the influence of natural environment factors. The weather can have an impact, as can the lighting on the image (Vidal-Tortosa and Lovelace, 2024). The existing literature provides an indication of the data that should be collected.

6.1.1. Built environment data

The built environment was obtained mainly through the use of the 'Basisregistratie Grootschalige Topografie' (BGT, 2024). This is a public dataset of the Netherlands, which is used to manage the design and configuration of the built environment. The dataset includes a range of objects, including buildings (e.g., residential houses, offices, schools), roads (e.g., motorways, parking spaces, cycling and walking lanes), water (e.g., rivers, lakes, canals, ponds), and greenery (e.g., trees, grass, plants). The BGT is accurate within a margin of 20 centimetres, providing an optimal approach for obtaining the environment behind the image. However, images may occasionally display built environment characteristics that are not visible through this data, such as temporary construction work. Furthermore, the built environment on a macro scale, is also known as it was used for categorising the images in Chapter 4.2. The built environment characteristics that are included are listed in Table 6.1. Figure 6.1 of the neighbourhood 'Oude Noorden' in Rotterdam demonstrates the high degree of accuracy of the BGT. The accuracy of the data is also verified using the street-level images.

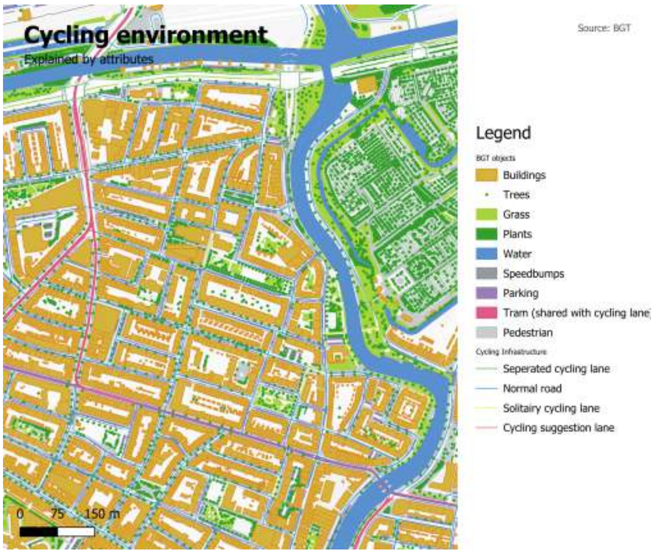


Figure 6.1: Built environment

6.1.2. Cycling infrastructure data

As previously indicated, the BGT also records information about road characteristics, such as pedestrian lanes, speed bumps, tram infrastructure and cycling lanes. However, there is somewhat less information about the cycling infrastructure itself. Therefore, other data sources were used. First of all, data from the Fietsersbond (2020) was available, which was used to categorise the images. This includes bike path type (see 4.4a) and pavement type.

Furthermore, for cycling lanes not shared with the car, data from the municipality was used. This data includes the width of the cycling lane, whether it is one-way or two-way, the intensity of cycling traffic during peak hours, the quality of the cycling lane, the colour and whether the width is adequate based on intensity and driving directions. The quality of the cycling lane was evaluated based on a number of criteria set by CROW (Centre for Regulations and Research in Civil Engineering and Traffic Engineering) (CROW, 2024). The bicycle intensities in rush hour were predicted by the Rotterdam traffic model Goudappel (2024). The entire dataset on separate bicycle paths is not publicly available; however, it can be reproduced with BGT (2024) and NDW (2024) data.

For cycling suggestion lanes and normal roads, where cyclists share the road with the car, the speed was obtained using the data from (Rijkswaterstaat, 2024). Based on the BGT, width, colour and pavement type were obtained. In addition, car intensities were also obtained based on the Omnitrans traffic model.

6.1.3. Weather and Light

The date and time of the capture of the street-level images are known. This allows the retrieval of the weather conditions by matching them with the date and time. The weather data is accessed via Visual Crossing (2024), a public dataset where hourly weather data for years back can be downloaded for free. A variable representing either sunny or cloudy weather was created.

In addition, the brightness value of each image was calculated using a python script. Low brightness (0 - 100) indicates a darker image, possibly taken with shadows or in a tunnel. Medium brightness (100–180) represents moderate lighting, often indicating normal daylight or well-balanced lighting. And high brightness (180–255) suggests a bright image, which might be taken in strong sunlight or well-lit conditions.

6.1.4. Population density

CBS has data about macro-level built environment variables, including population density (CBS, 2024a). Population density data is available for each district, neighbourhood, and municipality in the Netherlands. Figure 6.2 displays the population density for each neighbourhood in Rotterdam.

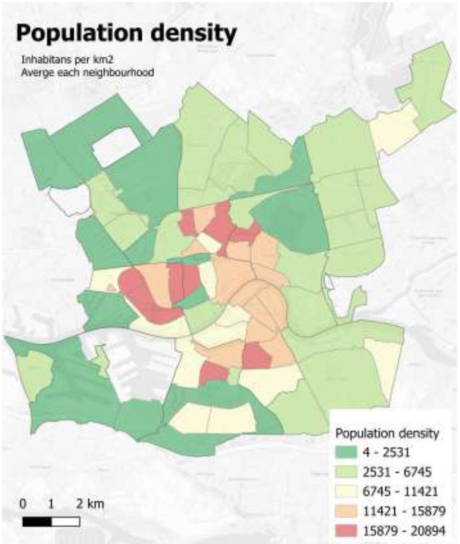
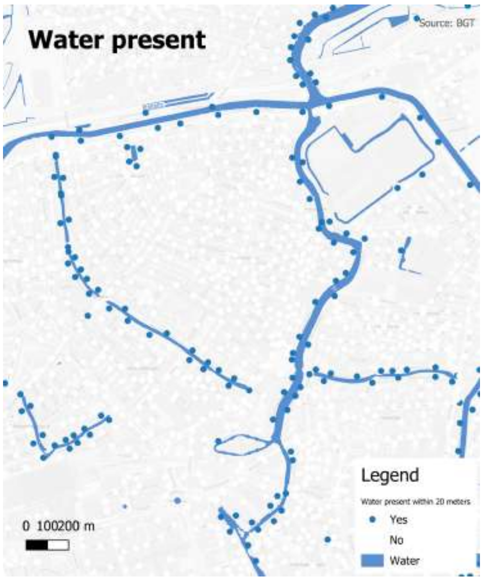


Figure 6.2: Population Density

6.2. Match attributes with the image

Once all the data has been collected, it needs to be matched with the images. For example, if the image displays water, the corresponding numerical value for water should be assigned the value of ”1”. Figure 6.3a illustrates the presence of water within a 20-metre radius. It can be observed that this method is accurate, as the images next to water are coloured blue. This process was also applied to all other attributes. For plants, grass, car parking and trams, a distance of 10 metres proved to be a good threshold. For attributes that are higher and larger, such as trees and buildings, a larger distance was employed, as these attributes remain visible even at greater distances. For trees, instead of a binary level with either no trees or trees, it is counted how many trees there are on a segment shown in Figure 6.3b. Since there are trees almost everywhere and trees are easy to count, this method was applied. However the difference in segment length introduces a degree of inaccuracy into this method.



(a) Water present

(b) Tree count per segment

Figure 6.3: Examples of matching the data with the image

Table 6.1 presents a comprehensive list of all the collected attributes, along with the data sources and the manner in which they are linked with the image.

Attribute	Attribute levels	Source	Link
Micro Built Environment			
Trees	Amount of trees	BGT	Segment buffer within 20 meters
Grass	Yes / no	BGT	Within 10 meters
Plants	Yes / no	BGT	Within 10 meters
Water	Yes / no	BGT	Within 20 meters
Buildings	Yes / no	BGT	Within 20 meters
Industrial buildings	Yes / no	BGT	Within 20 meters
Macro built Environment			
Built Environment type	Recreational Main road Access road Residential area Industrial area	BGT	No distance applied
Population Density	Inhabitants / km	CBS	Within the neighbourhood
Cycling Infrastructure			
Infrastructure type	Normal road Cycling suggestion lane Separated cycling lane Solitary cycling lane	Fietsersbond	Initial network
Pavement type	Asphalt Clinkers	Fietsersbond	Initial network
Parking	Yes / no	BGT	Within 10 meters
Width	Meters	BGT	Within 10 meters
Colour	Red / Not red	BGT	Within 10 meters
Tram on cycling lane	Yes / no	BGT	Within 10 meters
Traffic			
Car intensities	Numeric	Omnitrans	
Cycle intensities	Numeric	Omnitrans	
Car speed	NA 30 50	Rijkswaterstaat	
Other			
Weather	Sunny Cloudy	Visual Crossing	
Lighting	Numeric		

Table 6.1: Collected attributes

6.3. Descriptive analysis of the attributes

In order to see the frequency with which the various attributes can be observed in the images, as well as to determine whether these attributes are correlated, an analysis of the micro-built environment and the cycling infrastructure is conducted. The results of this analysis are presented in Table **??**, which shows the percentage of the attribute levels.

Attribute	Not present	Present			
Water	80%	20%			
Grass	52%	48%			
Plants	74%	26%			
House	7%	93%			
Industrial	95%	5%			
Parking	35%	65%			
Tram	99%	1%			
	Asphalt	**Clinkers**			
Pavement	30%	70%			
	Cloudy	**Sunny**			
Weather	63%	37%			
	0	**1 - 14**	**15 - 36**	**36 - 100**	**100+**
Trees	4%	54%	33%	6%	3%
	Normal road	**Suggestion lane**	**Separated lane**		
Cycling Type	77%	5%	18%		

Table 6.2: Descriptive Statistics of Attributes

Figure 6.4 illustrates the correlations between the attributes, which were calculated for validation of the data collection as well as to check for multicollinearity. Multicollinearity refers to the situation in which the independent variables are highly correlated with one another. When multicollinearity is present, it can have a number of effects and implications for further analysis. The presence of multicollinearity makes it challenging for the model to determine the unique contribution of each independent variable. Consequently, the coefficient estimates may become unstable and unreliable (Donath et al., 2012). When a multicollinearity diagnostic is considered, correlation coefficients between attributes is the most common tool for inspection used by statisticians (Vatcheva et al., 2016). Some investigators use correlation coefficients cut-off of 0.5 and above (Donath et al., 2012) but most typical cut-off is 0.80 (Berry, 1985).

A positive correlation can be observed between trees, grass, water and plants. This is also as expected, given that a river is often characterised by the presence of grass on the shoreline. In areas with a high tree density, such as recreational areas, the presence of grass and other plants is also frequently observed. Furthermore, a positive correlation can be observed between houses, parking and paving. This is also in accordance with expectations. It is common for houses to have parking spaces located in front of their doors. With regard to paving a distinction was made between asphalt (value 0) and clinkers (value 1). Residential roads with lots of houses and parking mostly have clinkers as pavement. For cycling type a distinction was made between normal roads (value 0), cycling suggestion lanes (value 1) and separated cycling lanes (value 2). It is notable that normal roads often have clinkers, while cycling lanes often have asphalt. The correlation between cycling type and pavement type is -0.39, which is the highest correlation. Furthermore, it can be observed that brightness and weather have a positive correlation, which is also expected. In addition, grass and water have a negative correlation with parking, pavement type and house which is also logical. The highest correlation of -0.39 is below the threshold of 0.8, indicating that there is no multicollinearity.

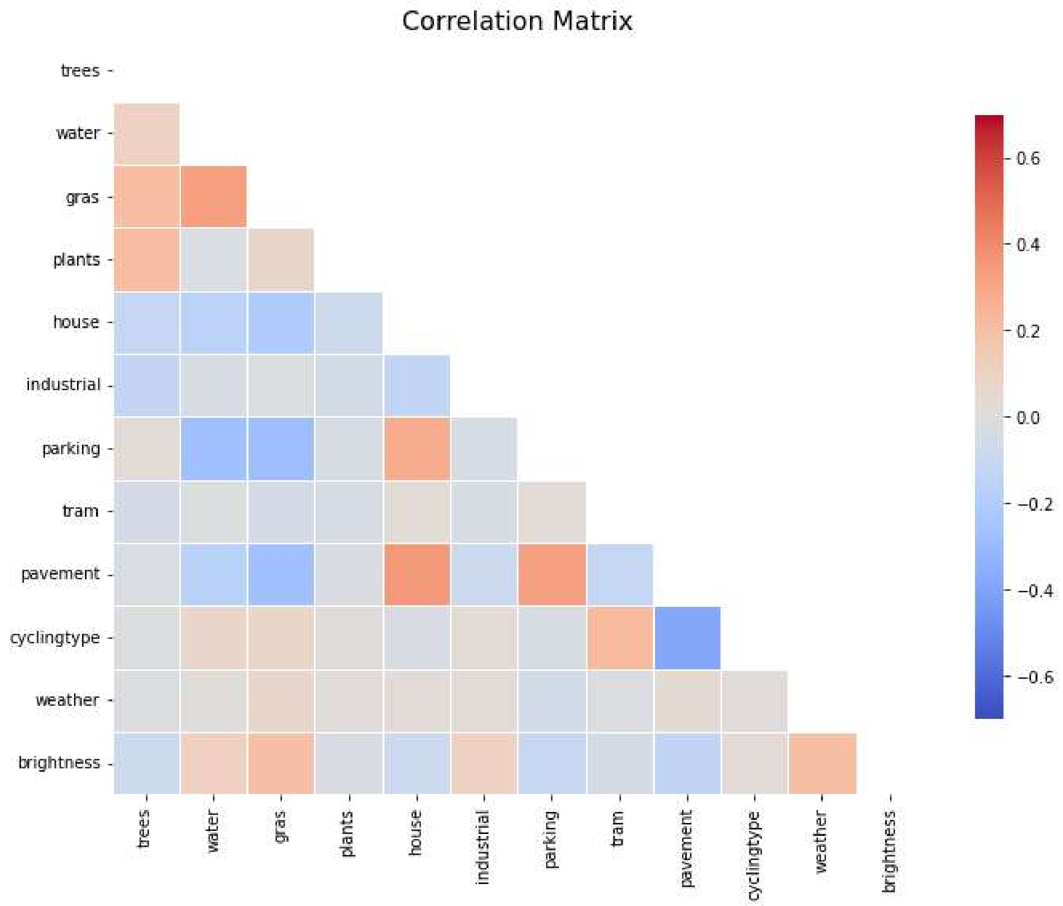


Figure 6.4: Correlations between the attributes

Cycling type is the only categorical variable. In the case of categorical variables, the chi-square test provides a better representation (Kearney, 2017). Consequently, a chi-square test was conducted to analyse the relationship between pavement and cycling type, as illustrated in Table 6.3. The results demonstrate a difference between the observed and expected frequencies, indicating correlation between the variables. The Cramér's V value of 0.376 suggests a moderate correlation between the variables, indicating that the attributes are related to some extent. Additionally, there is no evidence of multicollinearity, as Cramér's V is below the threshold of 0.5 (Akoglu, 2018).

Statistic	**Value**
Chi-Square Statistic	1370.95
P-value	4.32e-300
Cramér's V	0.376

Table 6.3: Chi-square statistics for cycling type and pavement

7 Results stated choice experiment

This chapter presents the results. Section 7.1 provides an overview of the respondents, offering insights into the characteristics of the individuals who completed the survey. Section 7.2 explains the process of training the cv-dcm. The estimation results of the different models are presented in Section 7.3. Section 7.4 details the outcomes of the cv-dcm, Section 7.5 focuses on the results of the cycling environment attributes model. Finally, Section 7.6 discusses the findings of the latent class model.

7.1. Descriptive analysis

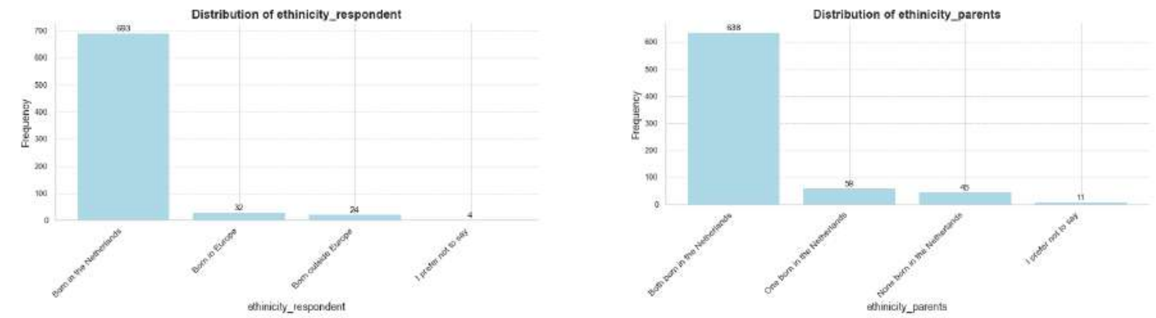
The survey was completed by 753 individuals through the panel company Cint (Cint, 2024) between the end of September and the beginning of October 2024. The respondents were financially compensated for their participation in the survey. The respondents in the study were individuals aged 18 years and above who engage in cycling. Individuals who do not cycle were unable to participate in the survey, as it is focused on cycling routes.

An effort was made to ensure that the sample was representative of the Dutch population. This was achieved by filtering the data in advance based on gender, age, and region. The number of individuals from each group required to complete the survey was determined through the data of CBS (CBS, 2024a), ensuring the survey's representativeness. Additionally, individuals who completed the survey so quickly (half of the questions within three seconds) that it was not possible to actually make a choice based on the attributes were filtered out. Respondents were asked to provide socio-demographic information and information about their cycling habits. In Appendix F, the distribution of each question is illustrated through a series of plots. The most notable of these are explained here.

7.1.1. Social demographics

The representativeness of the survey with respect to social demographics was evaluated by comparing the histograms of the survey with those of dam population (CBS, 2024b). The findings indicate that the survey is representative in terms of age, gender, education level, income and work distribution. For instance, around 33% of the respondents indicated that they are not currently employed which corresponds to the unemployment rate in Rotterdam (Corrected for elderly).

As can be seen by the histograms shown in Figure 7.1 the majority of respondents are born in the Netherlands (92%), and also the majority of parents of the respondents are born in the Netherlands (85%). The high proportion of Dutch respondents is due to the fact that Cint typically conducts surveys for the Netherlands in Dutch. The majority of their panel providers have a primary focus on Dutch respondents. The Rotterdam population consist of 44% individuals of Dutch origin (CBS, 2024b). Consequently, regarding to the migration background the survey is not representative of Rotterdam's population. Prior to the start of the survey, respondents were asked whether they engaged in cycling. There were 110 people who indicated that they do not cycle. The study of Durand et al. (2023) shows that individuals with a background of migration were less likely to engage in cycling. This could partly suggests that the inclusion of this criterion may have resulted in the exclusion of respondents with a migration background.



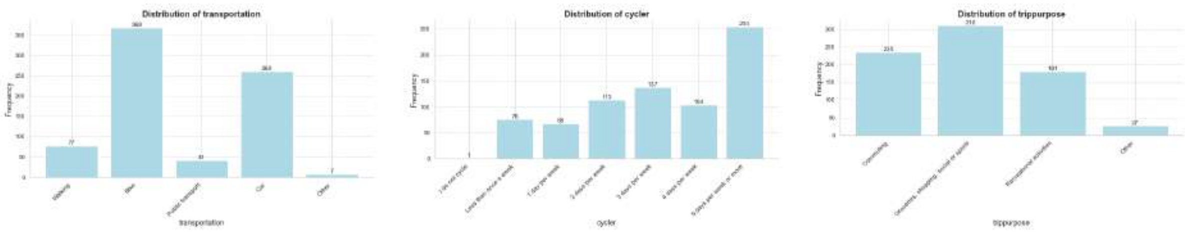
(a) Distribution of the ethnicity of the respondent

(b) Distribution of the ethnicity of the parents

Figure 7.1: Distributions of the ethnicity of the respondent and parents

7.1.2. Cycling habits

In addition to social demographics, respondents were also asked about their cycling habits. It was found that approximately half of the respondents indicated that cycling is their most frequently used mode of transport. Furthermore, two-thirds of the respondents cycle more than three times per week. A significant proportion of respondents indicated that their primary motivation for cycling is not work-related as can be seen in Figure 7.2c. One-third of the respondents indicated that their primary purpose for cycling is to commute to work or study, while two-thirds cycle for other purposes, including sports, shopping, recreational and social activities. Literature reveals that when the objective is leisure, the chosen route will likely be more aesthetically pleasing, whereas if the purpose is commuting, the chosen route will be mostly selected based on travel time (Yang et al., 2019).



(a) Distribution of modes

(b) Distribution of cycling rate

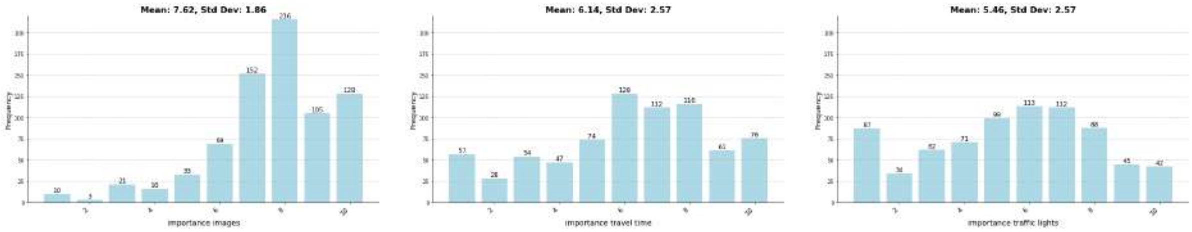
(c) Distribution of trip purpose

Figure 7.2: Distributions of cycling habits

Respondents had the possibility to fill in how they experienced the survey. Frequently, they said that they found it enjoyable and unique due to its image-based assessment. This suggests that respondents were interested and therefore did not just select a response at random. Further, they sometimes noted that the images were frequently busy in traffic and densely populated, which did not align with their own rural environments. It can be expected that individuals living rural will value cycling environment more than those living in an urban environment. Consequently, the responses may not fully reflect the characteristics of Rotterdam's population.

7.1.3. Self-reported importance

Respondents also had to report how important the attributes travel time, traffic lights and the image were for making decisions. It is note worthy that self-reported importance may not always align with actual decisions. However, this approach provides a valuable first insight into the underlying patterns. Figures 7.3 show the distribution of the self-reported importance of the attributes. The results demonstrate that, in general, respondents considered the image to be of greater importance than other factors. On average, the image was rated 7.6, while travel time was rated 6.1 and traffic lights 5.5. Notably, previous research by Verhoeven et al. (2018) and Bernardi et al. (2018) has indicated that a significant proportion of individuals do not differ from the fastest route. However, in this survey, a considerable number of respondents assigned greater importance to the cycling environment than to travel time.



(a) Self-reported importance of the image **(b)** Self-reported importance of the travel time **(c)** Self-reported importance of the traffic lights

Figure 7.3: Self-reported importance ratings

Correlations between the self-reported importance of attributes and other social demographics are examined to obtain an understanding of the groups that value cycling environment or travel time. Figure 7.4 shows the correlations between self-reported importance of attributes and the asked social demographics. Imptt means importance of travel time, imptl means importance of traffic lights and impimage means importance of the image. Correlations between all the social demographics can be seen in Appendix F.

The results demonstrate a positive correlation between age and the self-reported importance of the image, as well as a negative correlation between age and the self-reported importance of travel time and traffic lights. This is in line with the literature which indicates that older cyclists tend to place a higher value on road safety and the cycling environment than younger people (Heinen et al., 2010).

It can also be seen that those who frequently engage in cycling consider attributes to be of greater importance than those who do not cycle with the same frequency. In particular, traffic lights are considered more important by those who cycle frequently. Individuals who prioritise travel time also tend to consider the number of traffic lights, whereas the environment is relatively less important. Conversely, those who attach greater importance to the environment tend to consider travel time and traffic lights as relatively unimportant.

The frequency of cycling travel, the travel time to work, and when the purpose of cycling is commuting all influence the perceived importance of travel time and traffic lights positively and the perceive importance of the image negatively. This is in line with the study of Ton et al. (2017) that said that the impact of distance on route choice increases for commuting trips. In contrast, when individuals engage in cycling for purposes other than commuting, the importance of travel time and traffic lights is decreased. Those individuals assigned a higher value to the image. It can also be noted that people living in urban environments tend to place a higher value on travel time and the presence of traffic lights than those living in rural environments.

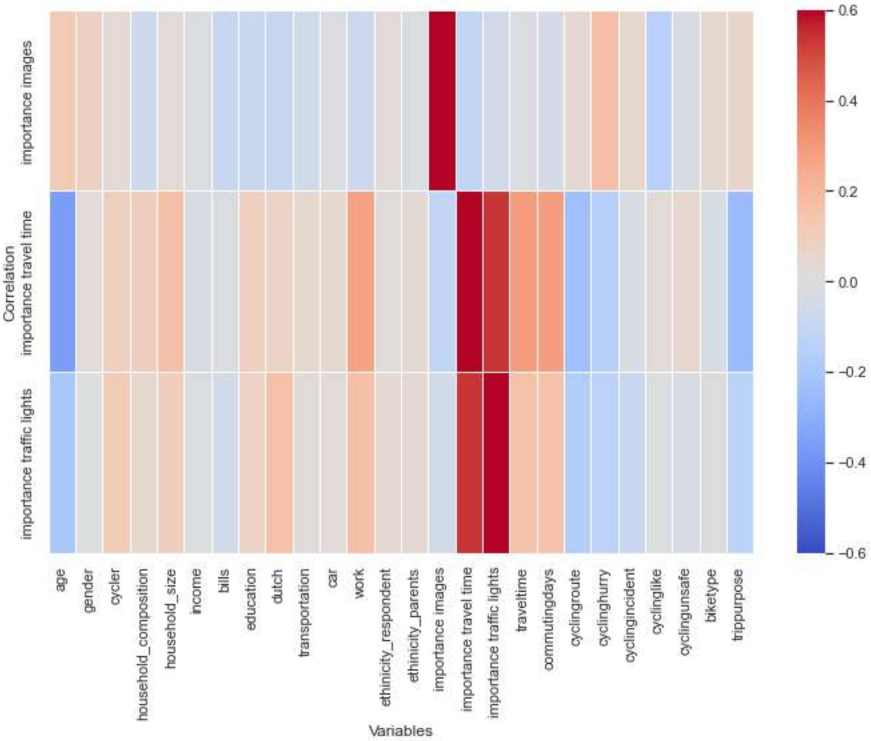


Figure 7.4: Correlations with the self-reported importance of attributes

7.1.4. Distribution for each choice situation

In total, there are 30 choice situations. The distribution of answers per choice situation is illustrated in Appendix G. The appendix also shows the distribution that was estimated in advance for each choice situation. It can be seen that the priors and the actual distribution are similar. This is to good as the use of inaccurate priors could have resulted in less efficient and biased parameters. It can also be seen that one choice situation has a distribution of more than 80% which indicates that there is a dominant alternative.

In order to gain further insight into how the survey questions were answered, a choice situation is examined in closer detail. Figure 7.5 illustrates a choice situation in which the distribution is approximately equal. The image of Route 1 is sorted as a separate cycling lane on a main road (Category 12). The image of Route 2 is sorted as a cycling suggestion lane on a access road, where cars can drive at a speed of 50 km/h (Category 3). The images are different each time, so in this example the cycling suggestion looks cycling friendly, though this is not always the case. Table 7.1 shows that 46% of the respondents selected route 1, which has a higher travel time and a higher number of traffic lights than route 2. This indicates that almost half of the respondents prioritise the cycling environment over traffic lights and travel time for this case.

Choice Situation	Route 1 (%)	Route 2 (%)
7	46	54

Table 7.1: Choice Situation Route Percentages

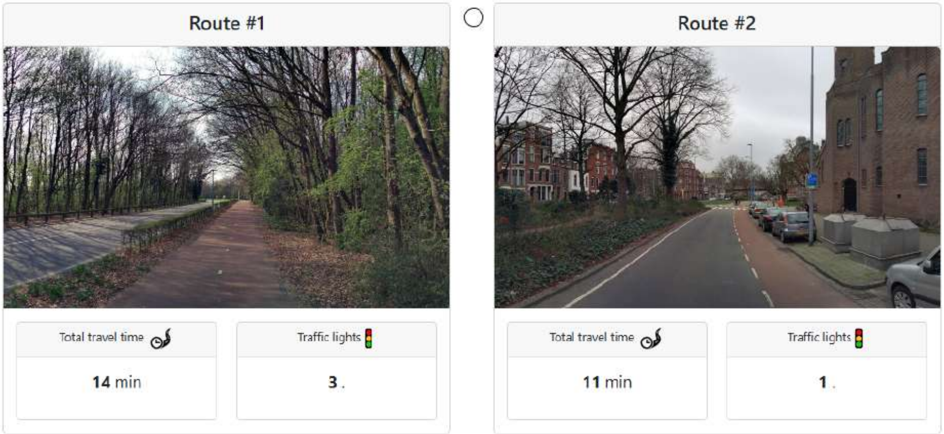


Figure 7.5: Analysis of choice situation 7

7.1.5. Images applied in the survey

As outlined in Chapter 4.2 the database contains approximately 13.000 images which are classified into fifteen categories. Within each category, the images are further divided into two different sets: a test set and a training set. The category with the lowest number of images includes 149 images, suggesting a high probability of image repetition. This probability varies across categories, with some categories having a higher probability than others. A total of 6.484 unique images were applied in the survey. As illustrated in Figure 7.6, approximately 2.000 images were used once. One image was observed to have been shown 23 times, representing the highest frequency.

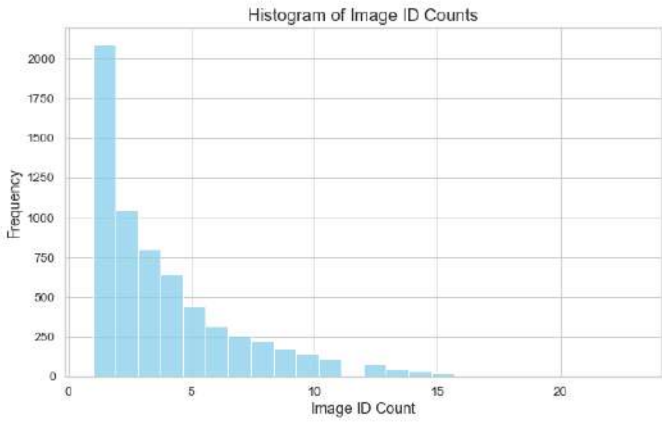


Figure 7.6: Distribution of image count that are applied in the survey

7.2. Training the cv-dcm

In order to train the cv-dcm, a pre-trained model was applied to reduce both the computational time and the data requirements. Transfer learning was used to start with a model that had already learned relevant visual features, thereby providing a good foundation. In particular, the DeiT base model (Touvron et al., 2021) was employed, which had been pre-trained on ImageNet (ImageNet, 2024), a comprehensive dataset comprising 1.2 million images. This approach allowed for the beginning of training from an already effective starting point, thereby ensuring both efficiency and model performance. The images now consist of a feature map of 1000 values, which contains most of the information that can be seen in the image and will be used for training the cv-dcm. The values of the feature map are converted to a normal distribution with the mean zero and the standard deviation 0.1.

7.2.1. Cross-entropy loss function

The feature map, combined with the numeric attributes, was estimated similarly to a classical discrete choice model, as described in Chapter 3.5 The primary goal was to identify the beta parameters for travel time, traffic lights, and the 1,000 elements of the feature map that would minimise the cross-entropy loss. The cross-entropy loss function aims to reduce the error between the actual and predicted outcomes (DataCamp, 2024), with a lower cross-entropy value indicating improved model performance. Minimising this loss is effectively equivalent to maximizing the log-likelihood (LL), as explained in Chapter 3.4. The cross-entropy loss function is presented in Formula 7.1. The second part of the formula is the L2 regularisation. The purpose of the L2 regularisation is to help prevent the model from overfitting by adding a penalty based on the size of the model's weights. The strength of this penalty is controlled by the parameter γ. The regularisation is only applied to the feature extractor weights w and not to the preference parameters β_m and β_k. Regularising these preference parameters could potentially introduce unwanted biases into the model (Cranenburgh and Garrido-Valenzuela, 2023).

$$w, \beta = \arg\min_{w,\beta} \left(\underbrace{\frac{1}{N} \sum_{n=1}^{N} \sum_{j=1}^{J} y_{nj} \log(P_{nj} | X_{nj}, S_{jn}, \beta) +}_{\text{Cross-entropy loss}} \underbrace{\gamma \sum_{r=1}^{R} w_r^2}_{\text{L2 regularisation}} \right) \tag{7.1}$$

7.2.2. Training and hyperparameter tuning

The cv-dcm has been implemented and trained using PyTorch. This was done by Associate Professor Sander van Cranenburgh (Cranenburgh, 2024). The methodology in this study is similar to that applied in the study of Cranenburgh and Garrido-Valenzuela (2023). PyTorch is a machine learning package that is frequently employed in the field of deep learning and computer vision research due to its ability to support GPU computing. The hyper parameters of the cv-dcm were determined through the utilisation of a heuristic search approach. A variety of optimisation algorithms, learning rates, batch sizes and regularisation settings have been tested in order to determine the optimal hyperparameters. A comprehensive hyperparameter tuning would have been the optimal approach, involving the testing of all possible combinations of optimisation algorithms, learning rates, batch sizes, and regularisation parameters. However, due to the high computational cost associated with training cv-dcm (and CV models in general), this was not a feasible option. Instead, the hyperparameters in Table 7.2 are identified as the most effective.

Hyperparameter	**Value**
Device	cuda
Optimisation algorithm	Stochastic Gradient Descent
Learning Rate	1×10^{-5}
Batch Size	5
L2 weight decay (γ)	0.1

Table 7.2: Hyperparameters for Model Training

7.3. Estimation results different models

Five models were developed to predict cycling route choice. Section 7.3.1 describes the models and shows the parameter estimates. Section 7.3.2 demonstrates the importance of the attributes.

7.3.1. Parameter estimates

Model 1 predicts the data with only information about traffic lights and travel time. This model was applied as a benchmark to assess the degree of improvement in prediction accuracy of the cv-dcm. Model 2 is the cv-dcm. The cv-dcm can accommodate choice tasks involving numeric attributes and images. Model 3 was then estimated using the predicted utility scores for each image of the cv-dcm. This was done to ensure consistency in the training process, as the cv-dcm was trained with backpropagation, while the other models were trained with the bgw method. In order to facilitate a comparison of the models, the cv-dcm was also estimated using this bgw method, which is more precise than back-propagation. To analyse which attributes of the cycling environment are deemed important, model 4 was estimated, which predicts separate built environment characteristics and infrastructure elements. Subsequently, model 5 was estimated, incorporating both the cv-dcm score and the infrastructure and built environment. In order to prevent overfitting, a training and testing set was applied. The parameters were trained on the training set and subsequently validated on the test set. Table 7.3 illustrates the estimation results of the various models. Notably, the models did not overfit the data, as evidenced by the minimal differences in rho-square between the training and test sets. For each model, travel time is expressed in terms of traffic lights. It can be seen that one extra traffic light can be compared to about one and a half minutes.

Model Equations

$$\text{Model 1:}\quad U_{in} = \underbrace{\beta_{tt}\, tt_{in} + \beta_{tl}\, tl_{in}}_{\text{Utility } tt \text{ and } tl} + \varepsilon_{in} \tag{7.2}$$

$$\text{Model 2:}\quad U_{in} = \underbrace{\beta_{tt}\, tt_{in} + \beta_{tl}\, tl_{in}}_{\text{Utility } tt \text{ and } tl} + \underbrace{\sum_k \beta_k \cdot z_{ikn}}_{\textit{Utility image feature map}} + \varepsilon_{in} \tag{7.3}$$

$$\text{Model 3:}\quad U_{in} = \underbrace{\beta_{tt}\, tt_{in} + \beta_{tl}\, tl_{in}}_{\text{Utility } tt \text{ and } tl} + \underbrace{\beta_s\, s_{in}}_{\textit{Predicted utility score (cv-dcm)}} + \varepsilon_{in} \tag{7.4}$$

$$\text{Model 4:}\quad U_{in} = \underbrace{\beta_{tt}\, tt_{in} + \beta_{tl}\, tl_{in}}_{\text{Utility } tt \text{ and } tl} + \underbrace{\sum_{ce} \beta_{ce} \cdot ce_{in}}_{\textit{Utility cycling environment attributes}} + \varepsilon_{in} \tag{7.5}$$

$$\text{Model 5:}\quad U_{in} = \underbrace{\beta_{tt}\, tt_{in} + \beta_{tl}\, tl_{in}}_{\text{Utility from } tt \text{ and } tl} + \underbrace{\beta_s\, s_{in}}_{\textit{Predicted utility score (cv-dcm)}} + \underbrace{\sum_{ce} \beta_{ce} \cdot ce_{in}}_{\textit{Utility cycling environment attributes}} + \varepsilon_{in} \tag{7.6}$$

Model 1: Travel time and traffic lights
Model 1 with only travel time and traffic lights shows a relatively low rho-square of 0.036, indicating that the model explains only a minor proportion of the data.

Model 2: cv-dcm
It can be observed that the rho-square of the cv-dcm is 0.101. This value is considerably higher than that of Model 1. It can therefore be concluded that the cv-dcm is capable of accurately predicting the utility of the images, and that the cycling environment exerts a significant influence on cycling route choice behaviour. A rho-square of 0.101 is not very high, yet still within an acceptable range. The observed parameters align with expectations, particularly in regard to the disutility of travel time and traffic lights. In Chapter 7.4 the cv-dcm is analysed in detail.

Model 3: Environment score estimated with bgw
The rho-square value for Model 3 is 0.115. Furthermore, the BIC value of this model is the lowest. It was anticipated that the beta parameter of the score would be equal to 1, given that the score of an image was already represented in utility by the cv-dcm. The difference can be attributed to the different optimisation techniques applied for each model. The cv-dcm was trained with backpropagation,

whereas the other models were optimised with bgw. It can be seen that Model 3 has a marginally higher rho-square than Model 2, suggesting that bgw can predict slightly more precise. In contrast, the computation time of backpropagation is way much shorter.

Model 4: Cycling environment attributes
Model 4 predicts the data based on the variables of travel time, traffic lights, infrastructure characteristics, the built environment, and weather. Rho-sqaure is 0.092, so the model does not outperform the cv-dcm. The cv-dcm highlights the significance of the cycling environment as a factor influencing individuals' decisions. However, it does not provide insights of specific elements within the environment as it is based on a neural network. This model is particularly useful because this model allows to isolate the impact of each attribute on the cyclist's choice. For a detailed examination of the parameters associated with Model 4, please refer to Chapter 7.5.

Model 5: Cycling environment attributes and environment score
Lastly, the predicted scores derived from the images were integrated with Model 4. Although this method yields the highest rho-squared, the BIC value is higher than that of the cv-dcm. Furthermore, it can be seen that numerous parameters in Model 4 have become insignificant. This is in accordance with expectations, given that the image score contains data about the built environment and infrastructure elements. During the analysis, it was observed that only the parameter of industrial area is still very significant, thereby contributing additional information. This suggests that while the cv-dcm provides good utility score predictions overall, it has room for improvement specifically in predicting utility scores for industrial areas.

		Model 1			**Model 2**			**Model 3**			**Model 4**			**Model 5**	
Model type		RUM-MNL			CV-DCM			RUM-MNL			RUM-MNL			RUM-MNL	
Estimation method		bgw			backpropagation			bgw			bgw			bgw	
Number of parameters		2			86m			3			15			16	
Train Set (N = 9135)															
Log-Likelihood		-6157			-5656			-5590			-5704			-5529	
Rho-squared		0.028			0.109			0.117			0.099			0.127	
Cross-entropy		0.674			0.617			0.612			0.624			0.605	
BIC		12332			-			11600			11208			11204	
Test Set (N = 2128)															
Log-Likelihood		-1421			-1326			-1306			-1339			-1298	
Rho-squared		0.036			0.101			0.115			0.092			0.120	
Cross-entropy		0.668			0.623			0.614			0.629			0.610	
BIC		2857			-			2635			2793			2719	
	est	**s.e.**	**p-val**	**est**	**s.e.**	**p-val**	**est**	**s.e.**	**p-val**	**est**	**s.e.**	**p-val**	**est**	**s.e.**	**p-val**
Parameters															
β_{tt}	-0.11	0.012	0.00	-0.10			-0.21	0.013	0.00	-0.23	0.0139	0.00	-0.23	0.014	0.00
β_{tl}	-0.23	0.021	0.00	-0.24			-0.30	0.022	0.00	-0.31	0.0215	0.00	-0.32	0.022	0.00
$\beta_{utilityscore}$							1.17	0.052	0.00				0.98	0.059	0.00
$\beta_{normalroad}$										0.00	Fixed	Fixed	0.00	Fixed	Fixed
$\beta_{suggestionlane}$										-0.05	0.054	0.37	-0.10	0.055	0.07
$\beta_{separatedlane}$										0.36	0.054	0.00	0.14	0.056	0.01
$\beta_{klinkers}$										-0.11	0.041	0.01	-0.05	0.043	0.25
β_{sunny}										0.09	0.033	0.01	0.04	0.034	0.22
$\beta_{brightness}$										0.04	0.008	0.00	0.02	0.008	0.01
β_{trees}										0.10	0.015	0.00	0.04	0.016	0.01
β_{water}										0.18	0.038	0.00	0.08	0.039	0.03
β_{house}										-0.31	0.049	0.00	-0.14	0.049	0.01
$\beta_{industrial}$										-0.63	0.059	0.00	-0.47	0.062	0.00
β_{gras}										0.24	0.038	0.00	-0.01	0.040	0.85
$\beta_{parking}$										-0.09	0.039	0.02	0.12	0.040	0.00
β_{tram}										-0.23	0.107	0.03	-0.19	0.107	0.07
β_{plants}										0.03	0.037	0.45	-0.05	0.038	0.17
Value of time	2.12	0.2522	0.00	2.38	?	?	1.43	0.1163	0.00	1.38	0.1034	0.00	1.39	0.104	0.00

Table 7.3: Model Comparison Table

7.3.2. Relative importance of attributes
This section presents the analysis of the relative importance of the attributes travel time, traffic lights and environment regarding cycling route choice. This also allows to analyse the relationships between the attributes. This was achieved by calculating the minimum and maximum utilities for these three

attributes, and therefore the maximum utility difference. These differences are scaled by relative importance, as illustrated in Table 7.4. This was conducted for models 1 to 4. Model 5 has not been included because there are numerous insignificant parameters for this model, which may result an incorrect representation. It is also worth noting that the relative importance also depends on the selected attribute levels. A higher range will naturally result in a higher utility difference and a higher relative importance. Nevertheless, these values are presented because attribute levels have been carefully considered as described in Chapter 5.

Figure 7.3 about the self-reported importance already showed that respondents considered the image to be of greater importance than travel time and traffic light. Table 7.4 confirms this finding, as it can be observed that the environment is perceived as being approximately three times more important than travel time. Additionally, travel time is deemed more important than the number of traffic lights.

In addition, it can be seen that model 2, the original cv-dcm, perceives the environment as even more important than models 3 and 4. Model 3 is the model that applies the predicted utility score of the cv-dcm to estimate cycling route choice using the bgw method. This model also gave a slightly higher rho-square than the original cv-dcm. It can therefore be concluded that the cv-dcm overestimates the environment and underestimates travel time.

The importance of the environment may be overestimated due to the presentation format, as images tend to attract more attention than numeric attributes. A more detailed analysis of this limitation is provided in the discussion.

	Model 1	**Model 2**	**Model 3**	**Model 4**
Model Type	RUM-MNL	CV-DCM	RUM-MNL	RUM-MNL
Estimation Method	bgw	backpropagation	bgw	bgw
Number of Parameters	2	86m	3	15
Relative Importance (%)				
Travel Time	59%	15%	23%	26%
Traffic Lights	41%	12%	11%	12%
Environment	-	73%	65%	62%

Table 7.4: Relative Importance and Model Performance Comparison

7.4. Results of the cv-dcm (Model 2)

Section 7.3 demonstrated that the cv-dcm is capable of accurately predicting utilities for cycling environments based on images. Building on this, the objective of analysing the cv-dcm is to gain insight into the types of environments in which individuals prefer to cycle, as well as those in which they do not, as reflected in the utility scores assigned by the cv-dcm.

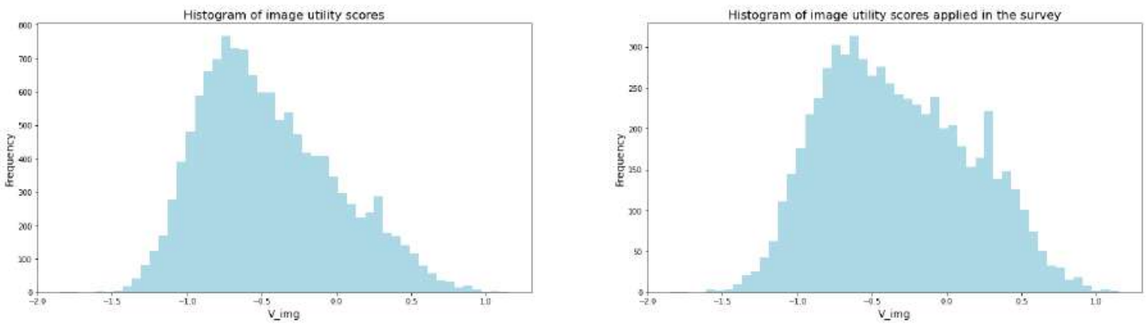
To achieve this, a comprehensive analysis of the cycling environment was conducted using a number of analytical techniques. Firstly, a spatial analysis is presented in Section 7.4.2, which demonstrates the locations in Rotterdam where individuals express a preference for cycling, and conversely, where this is not the case. Subsequently, a qualitative analysis in Section 7.4.3 was conducted to shed light on how different cycling environments are experienced. Thereafter, in Section 7.4.4, the impact of the built environment and cycling infrastructure on how people experience the cycling environment was examined. In Section 7.4.5, an even more detailed examination of the cycling infrastructure itself is conducted, taking into account factors such as width, colour, and pavement type. Finally, in Section 7.4.6, the model was applied to cycling infrastructure renovations to gain insight into how the cycling utility score changes with a renovation to the cycling infrastructure. Throughout all analyses, utility differences are analysed in conjunction with travel time and traffic lights, providing insights into the trade-offs cyclists make when selecting routes.

7.4.1. Descriptives of the utility score

The cv-dcm is applied to the dataset, consisting of 13.000 images and representing the entire cycling network of Rotterdam. The methodology employed to obtain these images is outlined in Chapter 4. For now, a concise overview will be given. The cycling network is constructed of segments. For each segment, greater than 3 meters, a point is created in the middle of the segment. Then, the nearest street-level image within a four-metre radius of a given point, is retrieved. Subsequently, images not intended for cycling were removed manually. Furthermore, for a detailed explanation about the working of the cv-dcm, please refer to Chapter 3.5

A predicted utility score is assigned to all 13.000 images. The utility score itself is of limited value as it does not have a defined scale. However, it can be used for identifying differences in utility scores between images. And since the location of the images is known, it can also be used for analysis, such as comparing neighbourhoods, cycling infrastructure, built environment etc. Further, the utility differences can be analysed in conjunction with the utility of travel time and traffic lights, thereby providing insights into the trade-offs that are made according cycling route choice. Figure 7.7 illustrate the distribution of the predicted image utility score for the survey and for the entire Rotterdam cycling network. It can be observed that the distribution of the survey is more uniform. This is logical due to the equal use of all image categories.

The utility score of dam cycling network ranges from -1.85 to 1.15. It is possible that the range may differ a bit when the model is applied to another city in the Netherlands. Furthermore, it can be observed that the mean utility is -0.5. It should be noted that a negative score does not necessarily indicate a poor cycling environment, as the utility score alone does not say much and the average is not zero.



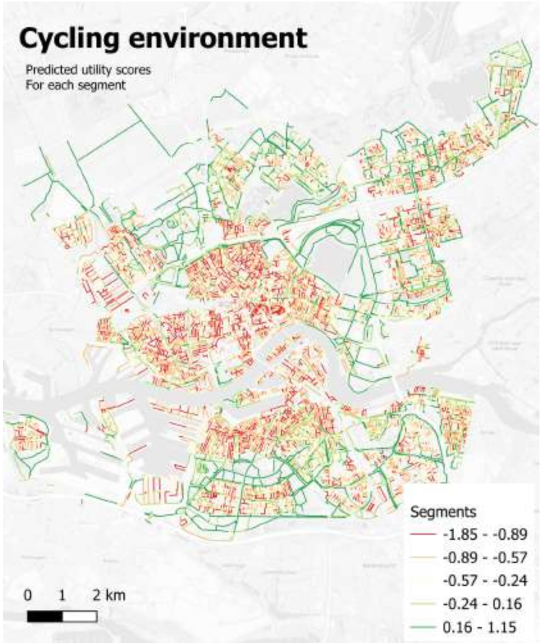
(a) Distribution of the predicted image utility score of dam cycling network

(b) Distribution of the predicted image utility score applied in the survey

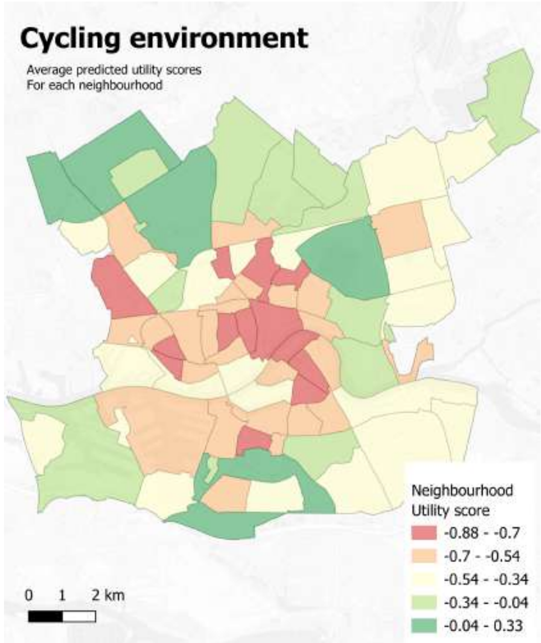
Figure 7.7: Distributions of the predicted image utility scores

7.4.2. Spatial distribution of the utility scores

The utility scores were plotted on a map of Rotterdam. The scores are divided into 5 clusters using the Jenks natural breaks method, which is a clustering technique to identify the optimal classification of values into different clusters. The method maximises the variance between classes and minimises the variance within each class (J. Chen et al., 2013). Figure 7.8a illustrates the utility score cluster for each cycling segment. Figure 7.8b illustrates the mean utility score cluster for each neighbourhood. It is notable that the centre of Rotterdam is coloured red and orange, while the surrounding regions are coloured yellow and light green. The recreational areas Kralingse Plas, Zuiderpark, Park Zestienhoven and an area to the upper left, which is mostly composed of meadows, are represented by a dark green colour. This contrast suggests that people may find green spaces more enjoyable for cycling than densely populated urban areas.



(a) Utility scores for each segment



(b) Average utility score per neighbourhood

Figure 7.8: Spatial distribution of the predicted utility scores

7.4.3. Qualitative analysis of the utility score

The qualitative analysis of the utility score is to gain deeper insights into the types of cycling environments that cyclists prefer. By examining the images with the highest and lowest utility scores, it is possible to identify the key differences in these environments. To obtain a more comprehensive view, an analysis of images based on natural grouping was performed, where images are grouped according to their predicted utility scores. Each cluster represents a range of utility scores, thereby highlighting how perceived cycling experience vary as cycling environments change.

Highest and lowest utility scores

In Figure 7.9 collages are presented, with the images having the highest predicted utility scores on the left and the images having the lowest predicted utility scores on the right. It is very noticeable that the images with the highest scores consist mainly of solitary cycling lanes located in an environment with trees, grass, and an absence of buildings or other roads. In contrast, images with the lowest scores are located in an environment with numerous buildings, vehicles, and roads shared with other traffic. Additionally, each image displays a van or a truck. The majority of the images appear to be situated within an industrial area. These results are consistent with the literature and hypotheses. Many people find it highly unpleasant to cycle past a truck which is understandable from a road safety perspective (Pokorny and Pitera, 2019). Also the study of P. Chen et al. (2018) concludes that individuals tend to favour cycling in an environment characterised by a high degree of greenery. And the study of Rossetti, Guevara, et al. (2018) says that cycling lanes where cyclists are separated from other traffic are preferred above no cycling lane.

The difference in utility between the highest and lowest scores is 3 utility points. Table 7.3 illustrates that the beta parameter of travel time is -0.11. This implies that, according to the model, individuals are willing to cycle 30 minutes extra to cycle in the environment represented by the top left of Figure 7.9b instead of the the environment represented by the top left of Figure 7.9a for a cycle trip of approximately 11 minutes. This appears somewhat extreme for those cycling to their work.

The highest utility images looks like to have more sunlight and brightness, although there are also some lowest utility images including sunlight. It was explicitly asked in the survey not to include weather in their decisions, however there is a chance that unintentionally weather had an influence. Additionally the presence of more light can also be explained by the fact that environments on the left side are more open than on the right side. Figure 7.10 illustrates the median utility for images with cloudy and sunny weather. It can be observed that the median is approximately equal, indicating that weather had a minimal impact on their decisions. Furthermore all images were captured between late February and early April. As evidenced in the images, trees are leafless and plants are not in bloom. This is the case across all images.

(a) Images with the highest predicted utility scores

(b) Images with the lowest predicted utility scores

Figure 7.9: Images with highest and lowest predicted utility scores

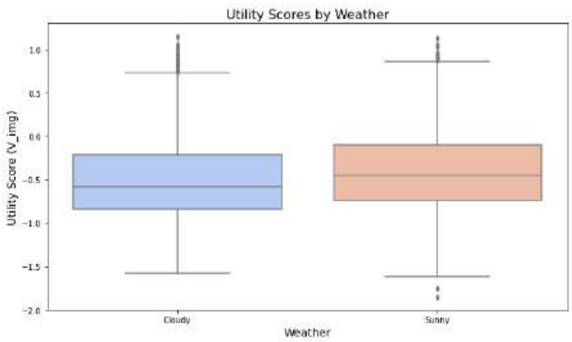


Figure 7.10: Average predicted utility score for cloudy and sunny weather

Visualisation and analysis of the five clusters

The objective of this analysis is to gain insight into the types of environments in which individuals prefer to cycle, as well as those in which they do not, as reflected in the utility scores assigned by the cv-dcm. Subsequently, a collage of 100 random images was generated for each cluster, as illustrated in Appendix H. The same clusters were applied as in Section 7.4.2. Figure 7.13 displays nine random images from each of the five clusters, providing a smaller overview. At first glance, it can be seen that greenery, including plants, trees, grass and water, becomes less visible as the cluster number increases. In contrast, there are more buildings and cars at higher cluster numbers. And the cycling infrastructure goes from a separated cycling lane to a cycling suggestion lane to normal roads at higher cluster numbers. Below is a detailed description and interpretation of the five clusters.

Cluster 1: Green Cycling Lanes (11.4%)

This cluster contains mainly cycling lanes in an environment with a high degree of greenery. It can be seen that solitary cycling lanes score higher while separated cycling lanes with a road next to them score slightly lower. A combination of grass, trees, plants and sometimes water can be seen in every image. Additionally, the images display a minimal presence of buildings and cars. When a building is present, it is often a well-maintained house situated in the background of the image. A similar observation can be made to cars; they are only occasionally visible in the background. As shown in Figure 7.8 these environments are mainly found in recreational areas (e.g. Kralings Plas), cycling lanes with a main function and areas outside the city centre.

Cluster 2: Green Cycling Lanes Main Road (17.7%)

In this cluster, greenery is still evident on every picture, including grass, trees and plants. The environment is somewhat more urban than in cluster 1. More houses can be seen, often on one side of the street. In contrast to Cluster 1, the presence of cars in the foreground is now sometimes observed. The cycling infrastructure is often a separated cycling lane, however some normal roads and cycling suggestion lanes can also be seen. The environment displays a high level of openness, characterised by the absence of narrow streets and unappealing buildings. The roads appear to serve mostly as a main road or access road. These environments are mainly found in Hillegersberg, Nesselande and Vreewijk.

Cluster 3: Urban Access Roads (23.7%)

In the third cluster, the environment becomes more crowded. More buildings can be seen than greenery. Whereas in cluster 2 grass could still be seen on almost every picture, that is no longer the case here. The roads seem to serve mainly as neighbourhood access roads or residential roads. Houses are also shown, but they are not typical residential streets. Often there are houses on one side of the street. It is also noticeable that the cycling infrastructure has changed compared to Cluster 1 and 2. Instead of separated cycling lanes, cycling suggestion lanes can be observed at the higher-utility within the cluster. Conversely, for the lower-utilities, more conventional roads are shown. This environment can be found in every neighbourhood.

Cluster 4: Urban Residential Roads (29.5%)

The fourth cluster is the largest cluster with 29.5% of all images. Many classic residential areas in the city where cars drive 30 km/h with clinkers are in this cluster. No grass can be seen, but there are often bushes and trees. Parked cars are also common. The villa neighbourhoods of Hillegersberg, for example, are not in this cluster, but in cluster 3. This cluster displays mainly urban residential areas, sometimes with a garden at the front.

Cluster 5: Very Urban Residential Roads or Industrial Areas (17.8%)

This cluster is dominated by residential areas with a lot of cars and vans. The streets are often narrow with relatively unattractive buildings on two sides, such as flats and small houses. There are hardly any trees, plants, grass and water. The number of cars is also very noticeable. There are also a number of industrial areas seen in the images. It is noticeable that whenever a van or truck appears in the image, the utility score is immediately very low. Densely populated residential areas such as Oude Noorden, Carnisse, Delfshaven, Bospolder, Crooswijk and Afrikaanderwijk are sorted in this cluster.

The analysis of the five clusters reveals a relationship between attributes such as greenery, buildings, and cycling infrastructure with the cv-dcm utility scores. Clusters with higher greenery, such as Cluster 1 and Cluster 2, with mostly cycling lanes, tend to receive higher utility scores. As the clusters progress towards more urbanised environments, such as, Cluster 4, and Cluster 5, with less greenery and more buildings, roads shift from separated cycling lanes to suggestion lanes and normal roads, resulting in lower utility scores. These findings highlight that natural, open environments with dedicated cycling infrastructure are valued higher, while more crowded, urban areas with normal roads are perceived as less desirable for cycling.

(a) Cluster 1 (0.16 to 1.15 utility) (11.4%)

(b) Cluster 2 (-0.24 to 0.16 utility) (17.7%)

(a) Cluster 3 (-0.57 to -0.24 utility) (23.7%)

(b) Cluster 4 (-0.89 to -0.57 utility) (29.5%)

(a) Cluster 5 (-1.85 to -0.89 utility) (17.8%)

Figure 7.13: Clusters based on the utility score

7.4.4. Quantitative analysis of the utility score

The preceding qualitative analysis provided a general view of how perceived cycling experience varies across different cycling environments. In contrast, this section delves deeper into the roles of various factors within the cycling environment. These factors include the types of cycling infrastructure and the built environment. By examining the relationships between utility scores and these factors, the analysis offers a more detailed view of how different factors of the cycling environment shape preferences. This, in turn, provides actionable insights for the design of cycling-friendly environments.

Relationship between cycling scores and cycling infrastructure

Previous studies have shown that cyclists prefer separated cycling lanes over cycling lanes shared with motorised traffic (Kaplan and Prato, 2015; Rossetti, Guevara, et al., 2018; Significance, 2022. The study of Rossetti, Guevara, et al. (2018) used a stated choice experiment with generated images.

However, in other studies, based on GPS data, it was found that cyclists are insensitive to cycling infrastructure (Ton et al., 2017; Bernardi et al., 2018). So the relationship between infrastructure and cycling route choice may vary by context. Furthermore, the findings of Misra and Watkins (2018) suggest that increasing speed of motorised traffic influence the decision to choose a cycling route negatively. It was observed that cycling rates decreased when vehicle speeds exceeded 30 km/h (Jestico et al., 2016; Verhoeven et al., 2018). These findings were particularly significant in situations where cyclists are not separated from other traffic (Winters et al., 2013). This study uses real-world images and the cv-dcm to assess how different types of infrastructure influence utility scores, and thereby route preferences. This can provide more accurate insights than generated images, as it reflects the actual environments cyclists encounter in practice.

Figure 7.14 illustrates the first quartile, median, and third quartile, among other statistical measures. It is demonstrated that separated cycling lanes and solitary cycling lanes are associated with a higher utility score than normal roads and cycling suggestion lanes. Additionally cycling suggestion lanes are assigned a higher score than normal roads. These findings highlight the impact of cycling infrastructure type on cycling route choice behaviour. Notably, the utility scores for separated cycling lanes are considerably higher than for cycling suggestion lanes, indicating that cyclists place a high value on separated cycling lanes. From a policy perspective, this analysis provides strong support for the construction of separated cycling lanes on roads where urban planners aim to improve the cycling experience.

Furthermore, Figure 7.14 indicates that the speed of motorised traffic has no impact on the utility score, as the scores for cycling suggestion lanes 30 and 50 are essentially identical, and the same is true for normal road 30 and 50. This outcome may be attributed to the survey design, as information about speed was not explicitly provided. Instead, it was assumed that participants would infer speed from the images. However, it seems that speed was not effectively inferred from the images alone, leading to its limited influence. Therefore, while this study suggests that speed is not a significant factor, it remains possible that speed of motorised traffic plays a role in cycling route choice in reality.

The difference in median utility between normal roads and separated cycling lanes is approximately 0.8. The beta parameter of travel time is 0.11, so according to the model, individuals are willing to cycle about 8 minutes extra to cycle on a separated cycling lane instead of a main road for a cycling trip of around 11 minutes. However, the built environment is not controlled in this analysis, which may result in an overestimation of this effect. For a more detailed discussion on this limitation and how it is addressed, please refer to Section 7.4.4.

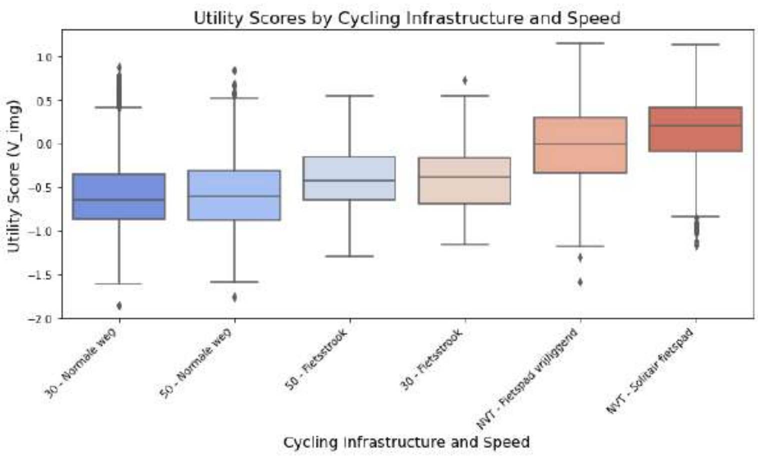


Figure 7.14: Utility scores by cycling infrastructure

Relationship between cycling scores and built environment

Previous studies suggests that cyclists favour routes with mixed land use, trees, other greenery, and urban features, with greenery being particularly influential (Heinen et al., 2010; Wang et al., 2016; Yang et al., 2019; P. Chen et al., 2018). However, their impact is context-dependent and sometimes inconsistent. While there have been studies that have included the built environment for the purpose of analysing cycling route choice in a stated choice experiment, this has been done with the built environment as text descriptions (Liu et al., 2021; Significance, 2022), which is challenging for respondents in terms of interpretation (Elu et al., 2021). The cv-dcm offers an accurate and realistic approach to evaluate the influence of the built environment on cycling route choice.

The analysed built environment characteristics are consistent with those applied for designing the stated choice experiment. These include industrial areas, residential areas, access roads, main roads and recreational areas. Figure 7.15 illustrates that recreational areas are assigned high utility scores. Similarly main roads were found to receive high scores. Main roads mostly have a separated cycling lane, more greenery, a limited number of buildings and a greater degree of openness. This explains the high score. To a somewhat lesser extent, the same applies to neighbourhood access roads. Interestingly, residential and industrial areas receive similar scores, with industrial areas scoring slightly worse. It was initially expected that residential areas would perform better, as previous research suggests that cyclists may appreciate urban features (Yang et al., 2019). However, residential areas are often characterised by dense building structures and clinker roads, which may reduce the attractiveness of these routes for cyclists.

Furthermore, the influence of the built environment on cycling route choice is stronger than anticipated, given that the literature suggested that built environment effects are often weak or mixed. As illustrated in Figure 7.15, the difference in median utility score between the industrial and recreational areas is 1.1, which is a higher difference than in Figure 7.14. However, the cycling infrastructure is not controlled in this analysis, which may result in an overestimation of this effect, as recreational areas are often solitary cycling lanes and industrial areas are often normal roads.

From a policy perspective, this analysis highlights the importance of greenery in cycling environments. The high utility scores for recreational areas indirectly demonstrate the positive impact of trees, grass, and plants on route attractiveness. The incorporation of such elements into urban cycling routes improves the cycling experience. Further insights into the micro-built environment are presented in Section 7.5, which explores how features like street-level greenery, buildings and cycling lane type influence cycling route choice behaviour.

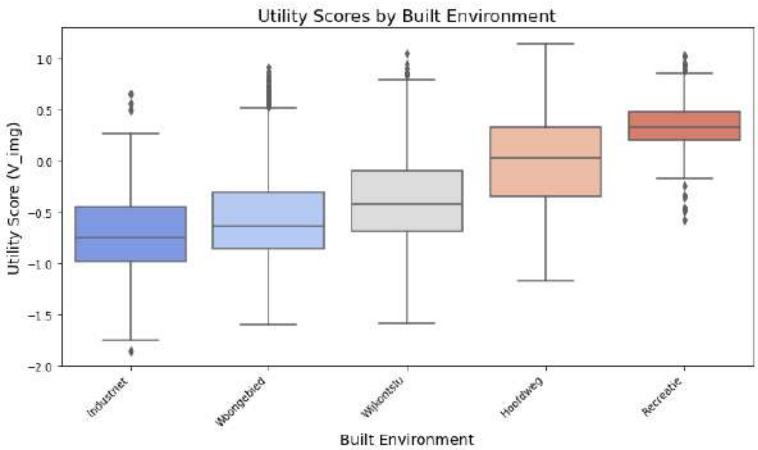


Figure 7.15: Utility scores by built environment

Relationship between cycling scores and cycling infrastructure (controlling for the built environment)

Nonetheless, as also indicated in the previous analysis, there is a correlation between cycling infrastructure and the built environment, including the presence of greenery and buildings as shown in Figure 7.16. For instance, a residential area is typified by the presence of normal roads and a lot of buildings. Neighbourhood access roads are often cycling suggestion lanes with lots of houses as well and more greenery. The majority of main roads have a separated cycling lane with few houses and greenery, while recreational areas often contain solitary cycling lanes.

This overlap between cycling infrastructure and built environment poses a challenge in interpreting the results from Section 7.4.4. For example, the high utility scores for solitary cycling lanes could be attributed to the type of cycling lane itself or the green environment in which they are typically found. It remains therefore unclear whether the utility scores are a result of the infrastructure, built environment, or a combination of both. To address this, this analysis was conducted. By controlling for the built environment, it becomes possible to identify the independent effect of cycling infrastructure on utility scores.

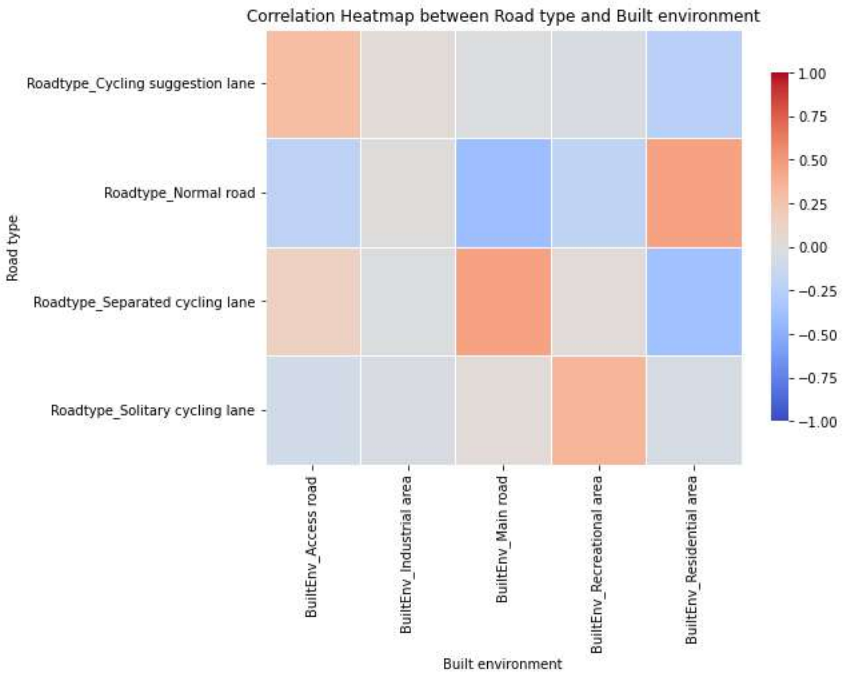


Figure 7.16: Correlation between cycling infrastructure and built environment

The municipality of Rotterdam is particularly interested in evaluating how different cycling infrastructure types perform on urban routes frequently used by cyclists for commuting. These roads are characterised by limited space, high levels of cyclist and traffic intensity, and a diverse range of infrastructure types. Understanding what defines a good cycling lane in this context is crucial for creating cycling-friendly environments in areas where they are most needed.

Chapter 6 presents the data gathered from the built environment and cycling infrastructure. This information is used to keep the built environment constant. The environment of investigation are neighbourhood access roads in densely populated urban areas with houses situated on either side of the road. The table 7.5 illustrates the specific parameters that were applied in the filtering process.

Parameter	Value
Built environment	Access road
Population density	$\geq$ 11420 inhabitants per km2
Grass	Not present
Water	Not present
Trees	$\leq$ 3
Pavement	Asphalt
Plants	Not present
Weather	Cloudy
Parking	Present
House	Present

Table 7.5: Filter Parameters and Their Values

Figure 7.17 shows 25 randomly selected images and their predicted utility scores for neighbourhood access roads in densely populated areas. It can be observed that the built environment in most images is fairly consistent, while the cycling infrastructure varies. The top left image shows the lowest score, gradually transitioning to the highest score in the bottom right image. There is a noticeable progression from roads that are shared with cars to cycling suggestion lanes marked with a dashed white line, then to red cycling suggestion lane, and finally to separated cycling lanes. The increasing utility score indicates that as cycling infrastructure becomes more dedicated and separated from car traffic, it is perceived more favourably by cyclists. Figure 7.18 shows that cyclists really value separated cycling lanes over cycling suggestion lanes at neighbourhood access roads in dense areas. Notably, the difference in the predicted cycling utility score is 0.16, which is equivalent to 1.5 minutes. So the average cyclist would detour for a 1.5 minutes to cycle on a separated cycling lane instead of a cycling suggestion lane for this cycling environment for a cycle trip of approximately 11 minutes.

From a policy perspective, these findings highlight the importance of separated cycling lanes on neighbourhood access roads in dense urban areas. Policymakers should prioritise the construction of separated lanes where possible in these areas. When space is limited, upgrading normal roads without dedicated cycling lanes to cycling suggestion lanes can still enhance the cycling experience.

Figure 7.17: Images and their predicted utility score on urban access roads

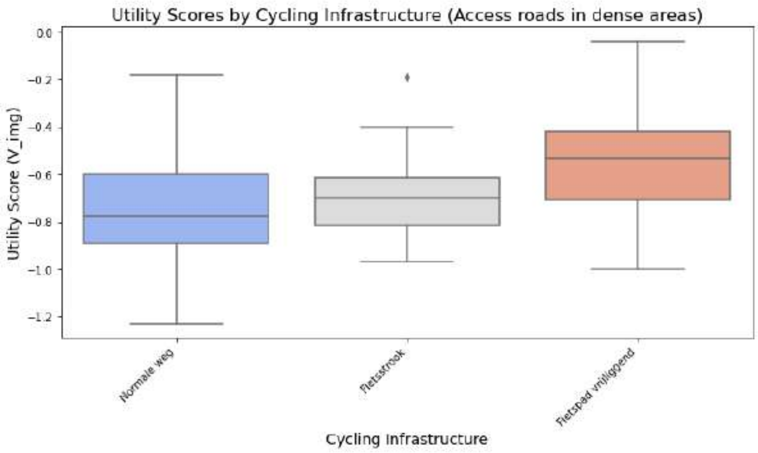


Figure 7.18: Utility scores by cycling infrastructure on urban access roads

7.4.5. Analysis of infrastructure characteristics on the utility score

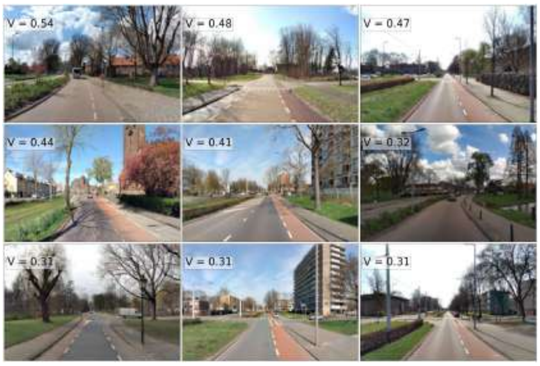
In Section 7.4.4 built environment and cycling infrastructure type is analysed. Building on these insights, this Section delves deeper into the specific characteristics of separated and cycling suggestion lanes. The municipality of Rotterdam is particularly interested in understanding how characteristics such as width, colour, and pavement influence cyclists' experience. A substantial amount of data is available regarding the characteristics of separated cycling lanes and cycling suggestion lanes.

In a stated-choice experiment with text-based route descriptions, Liu et al. (2021) highlighted that cyclists tend to prefer wider cycling lanes. Moreover, DTVConsultants (2023) demonstrated that wider lanes facilitate easier manoeuvring and safer distances from motor traffic for cyclists. This is also consistent with the CROW guidelines, which recommend wider lanes on routes with high cyclist intensity or interaction with other vehicles (Embassy, 2023). However, Stewart and McHale (2014) found that lane width did not influence motorists' choice of overtaking distance, indicating that its impact on cyclist experience and safety is not always straightforward. Regarding the colour of the cycling lane, several studies have identified the benefits of red cycling lanes, which are a common feature of the Dutch transport infrastructure. The use of red in these lanes has been shown to enhance safety and improve traffic flow (Bouwgrondstoffen, 2024). The study of Vera-Villarroel et al. (2016) found that red cycling lanes were perceived as safer and more appealing than lanes with other colours, thereby highlighting the role of colour in improving people's perceptions, especially in terms of likeness and familiarity. However, the study of Karlsen and Fyhri (2020) found that preference between colours varied based on individuals' familiarity with coloured cycling infrastructure. Regarding pavement type, the study by Kaparias et al. (2024) highlights that cyclists prefer asphalt over other pavement types, as it provides a smoother, safer, and more comfortable riding experience.

Cycling suggestion lane analysis

First cycling suggestion lanes are analysed. A cycling suggestion lane is a lane adjacent to a car lane, marked by a painted line and often painted surface. In Figure 7.19 collages are presented, with the images having the highest predicted utility scores on the left and the lowest predicted utility scores on the right. It is noticeable that high utility scores show a prevalence of grass, trees and an absence of cars, whereas low utility scores show urban environments with a prevalence of buildings, cars and vans and an absence of greenery. Additionally, images on the left side of the collage appear to have more lighting than those on the right. In terms of cycle lanes, high utility scores frequently display a broken line and red lanes, while low utility scores often show a broken line with no red colour.

The image collage especially highlights that greener environments (grass, trees) receive higher utility scores, which supports the idea that the natural environment plays a more prominent role than the characteristics of the infrastructure.



(a) Cycling suggestion lanes with the highest predicted utility scores

(b) Cycling suggestion lanes with the lowest predicted utility scores

Figure 7.19: Cycling suggestion lanes with highest and lowest predicted utility scores

In order to analyse cycling suggestion lanes, the characteristics of width, colour and the pavement type were taken into account. Firstly, it is essential to analyse the correlations between the characteristics of cycling suggestion lanes and the built environment. The correlations between cycling lane characteristics and built environment were found to be below 0.2, indicating minimal correlation. Therefore, all cycling suggestion lanes were included in the analysis. However, a strong correlation of above 0.8 was identified between pavement and colour of the cycling lane, in line with expectations (clinker lanes are mostly the same colour as the road). Consequently, these pavement and colour variables were combined.

Figure 7.20a displays the predicted utility score by width of the suggestion lane. The correlation between the predicted utility score and width is 0.07, indicating that there is an negligible relationship between the two variables. Figure 7.20b displays the predicted utility score by colour and pavement type. These results are also somewhat questionable, as the clinker roads achieved a higher score than the asphalt roads. Furthermore, the colour of the road has no impact, contrary to the literature and expectations.

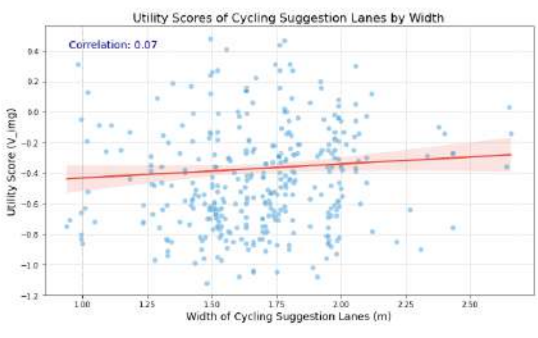
The absence of significant results for the relationship between utility scores and characteristics of cycling suggestion lanes (such as width, colour, and pavement type) could be attributed to several factors. The images demonstrate a lack of other cyclists, as illustrated in Figure 7.19. The study of Greibe and Buch (2015) indicates that cyclists prioritise width more when intensity is high. Consequently, this study posits that width is not a significant factor in cycling route selection when there are minimal other cyclists on the cycling lane. If there were many other cyclists, it is plausible that the width would have been a significant factor.

Despite the minimal correlation observed between built environment and infrastructure characteristics, it is plausible that a correlation exists. The image analysis suggests that clinker cycling suggestion lanes are more frequently located on roads with a relatively lower traffic volume than asphalt cycling suggestion lanes. So maintaining a completely consistent built environment is essential for accurately scoring these characteristics. The analysis presented in Chapter 7.4.6 investigate whether changes in the colour and width of cycling suggestion lanes impact the cycling experience when the built environment remains unchanged.

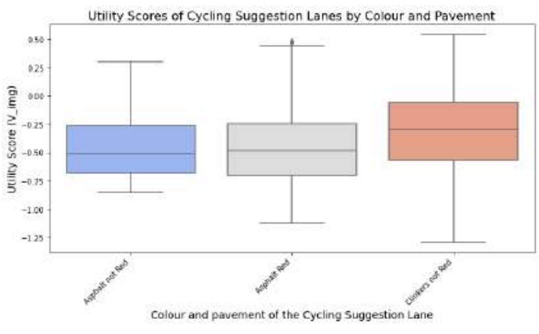
Additionally, the dataset utilised is not entirely accurate. The data is focused on administrative operations. Cycling lanes with similar asphalt to the road are often excluded in the data and subsequently excluded from this analysis. This results in the exclusion of cycling lanes with only a white line. The limited data points may be insufficient for conducting a comprehensive analysis.

The cv-dcm may struggle to distinguish subtle features like dashed white lines or differences in pavement type, especially in complex visual environments. As a result, these lane characteristics may not be accurately captured in the feature maps, limiting the model's ability to predict their influence on utility.

Lastly, it is also possible that these characteristics exert minimal influence on the selection of cycling routes. Cyclists may focus more on factors like travel time, road type, and built environment, rather than details like lane markings or colour changes.



(a) Utility scores by width of the cycling suggestion lane



(b) Utility scores by colour and pavement of the cycling suggestion lane

Figure 7.20: Cycling suggestion lane analysis

Separated cycling lane analysis

Having analysed cycling suggestion lanes, the following section delves into separated cycling lanes to determine if the impact of width, colour, and pavement is more prominent for this type of infrastructure. In Figure 7.21 collages are presented, with the images having the highest predicted utility scores on the left and the lowest predicted utility scores on the right. The results are similar with that of the previous as high scores are characterised by a prevalence of greenery, including trees, grass and plants. And low scores are characterised by an urban environment, including cars, houses and vans.

(a) Cycling lanes with the highest predicted utility scores

(b) Cycling lanes with the lowest predicted utility scores

Figure 7.21: Cycling lanes with highest and lowest predicted utility scores

This analysis also considered the impact of width, colour and pavement type on the cycling experience now in the context of separated cycling lanes. Again, it was decided not to look specifically at urban access roads as described in 7.5 as there were only a few separated cycling lanes left. Correlations between the characteristics of separated cycling lanes and the built environment are checked. The results demonstrated a significant correlation between pavement, width and the built environment. For numerous elements, the correlation coefficient exceeded 0.3. Cycling lanes in areas with a high degree of green space are frequently wider than cycling lanes in urban environments. Consequently, it is not feasible to include all cycling lanes in the analysis, as this would result in a biased representation.

An attempt was made to control for the built environment by focusing on specific areas, such as recreational. These analyses revealed no correlation between cycling lane width and utility scores. The same counts for colour and pavement type. This may be due to similar limitations as for cycling suggestion lanes, including the absence of other cyclists in images, the difficulty of isolating these characteristics from the built environment and limitations of the cv-dcm. In Chapter 7.4.6, the built environment is held entirely constant to better examine the influence of these characteristics on utility scores.

7.4.6. Renovations of the cycling infrastructure

In the previous section, the analysis focused on how various cycling infrastructure characteristics and types influence the perceived cycling experience. However, these analyses were limited by the variability in the built environment, which could have influenced the results. To address this, the following section evaluates the impact of actual infrastructure renovations in Rotterdam, where the built environment is kept more constant.

The municipality of Rotterdam is taking steps to encourage more people to cycle. One of these measures involves improving the cycling infrastructure by constructing separated cycling lanes and cycling suggestion lanes. Additionally, the municipality aims to redesign urban boulevards to create a better balance among different modes of transport, providing more space for cyclists.

In recent years, several improvements to cycling infrastructure have already been made. The Coolsingel, for instance, serves as an example of an urban boulevard that has been redesigned with more green and more space for cyclists (West8, 2024). Additionally, separated cycling lanes and cycling suggestion lanes have been constructed or improved. These interventions were intended to encourage cycling and improve cyclists' comfort and sense of safety. However, quantifying the impact of these improvements has been challenging and therefore post-renovation evaluations are often missing. The cv-dcm offers a promising solution for this. By comparing utility scores before and after renovations, the value that cyclists place on these changes can be quantified. This approach provides data-driven insights for future decision-making, ensuring that infrastructure investments align with cyclists' preferences and contribute to safer, more enjoyable cycling environments.

A number of renovations were identified for further consideration based on certain criteria. First, a range of different renovations was chosen. Further, it is essential that the weather and the number of cars are almost identical in the images, ensuring that these factors do not influence the score. Additionally, images of before and after the renovation must have been taken on the cycling lane. It was notable in the analysis that many separated cycling lanes in the city centre are relatively narrow and that there were often no images taken on these cycling lanes prior to renovation, such as on the Coolsingel. This may be attributed to the fact that the cycling lanes were too narrow for the vehicle from which the images were taken.

Based on these criteria, the following renovations were selected: Walenburgerweg, Poelenburg, Linker Rotterkade and Piekstraat. Figure 7.22 shows the location of these renovations. The before and after images of the renovations were rated by the model with a predicted utility score. The difference in utility shows how the renovation is perceived by the cyclists.

Figure 7.22: Selected renovations

Walenburgerweg

The Walenburgerweg is a busy neighbourhood access road in the Provenierswijk, Rotterdam North. In 2023, the cycling lane was widened and painted red. Further, the speed limit was modified from 50 km/h to 30 km/h. Although, this is not really noticeable from the images. Figure 7.23 illustrates the pre- and post-intervention conditions. Furthermore, the number of cars in the image, the weather conditions and the lighting are almost identical.

The image taken prior to the renovation is rated with a utility score of -0.77. The image taken after the renovation is rated with a utility score of -0.27. This represents a difference in utility of 0.5, indicating that the combination of widening the cycling lane and the red colour is preferred by cyclists. The beta parameter of travel time is -0.11, indicating that people are willing to cycle for an additional five minutes on the new cycle infrastructure rather than the old cycle infrastructure for a cycle trip of approximately 11 minutes.

Figure 7.23: Walenburgerweg

Poelenburg
The street Poelenburg is located in Zuidwijk in Charlois. On one side of the road there is a residential area and on the other there is a recreational area. A separated cycling lane was built here in 2022. Actually, this was the only separated cycling lane where before and after images could be compared. Figure 7.24 illustrates the pre- and post-intervention conditions. It can be seen that the number of cars in the image, the weather conditions and the lighting are almost identical.

The image taken prior to the renovation is rated with a utility score of -0.06. The image taken after the renovation is rated with a utility score of 0.16. This represents a difference in utility of 0.22, indicating that a separated cycling lane is preferred by cyclists. The beta parameter of travel time is -0.11, indicating that people are willing to cycle for an additional two minutes on the new cycle infrastructure rather than the old cycle infrastructure for a cycle trip of approximately 11 minutes.

It can be observed that this is a smaller utility difference than that seen in the Walenburgerweg example. This may be attributed to the non-linear relationship between utility score and infrastructure. The old infrastructure is more satisfactory for cycling than in the Walenburgerweg example as shown with the utility score. It is plausible that when the existing infrastructure is already satisfactory, individuals are less willing to take a detour to cycle on the new infrastructure. Additionaly, grey cycle lanes may be perceived as less appealing for cycling than red cycle lanes. This could also explain the relatively smaller difference in utility.

Figure 7.24: Poelenburg

Linker Rottekade
The Linker Rottekade is a neighbourhood access road in Old-Crooswijk. Cycling suggestion lanes were constructed in 2022. Figure 7.25 illustrates the pre- and post-intervention conditions. There is slightly more light in the pre-intervention image, but in terms of cars and weather, the images are roughly similar.

The image taken prior to the renovation is rated with a utility score of -0.32. The image taken after the renovation is rated with a utility score of -0.10. This represents also a difference in utility of 0.22, indicating that the cycling suggestion lane is preferred over a normal road by cyclists. People are willing to cycle for an additional two minutes on the new cycle infrastructure rather than the old cycle infrastructure for a cycle trip of approximately 11 minutes.

Figure 7.25: Linker Rottekade

Piekstraat
This final example will examine the renovation of Piekstraat, which is situated in the Feijnoord neighbourhood. While the Piekstraat serves a a neighbourhood access road, it is also situated somewhat remotely in an industrial environment. Cycling suggestion lines were constructed in 2022. Figure 7.26 illustrates the pre- and post-intervention conditions. There are more cars seen in the post-intervention image, but in terms of weather, light and other characteristics the images are roughly identical.

The image taken prior to the renovation is rated with a utility score of -0.81. The image taken after the renovation is rated with a utility score of -0.95. This represents a disutility of 0.14, indicating that a normal road is preferred over the cycling suggestion lines by cyclists. This outcome differs from the expectations. It is plausible that the majority of cars shown in the post-intervention image provide a greater degree of disutility than the cycle lane offers in terms of utility. Furthermore, it can be observed that the cycle lane is marked with white lines. It is likely that cyclists would prefer to have more than just the lines on the street, such as a red colour and a slightly wider lane. Additionally, it is possible that the model has difficulty recognising these lines as a cycle lane, given that the majority of cycle lanes are coloured red.

Figure 7.26: Piekstraat

Table 7.6 highlights how renovations affect predicted utility scores and translate into differences in travel time.

Location	Renovation	Before	After	Difference	In Terms of Travel Time
Walenburgerweg	Suggestion lanes widened & coloured red	-0.77	-0.27	-0.5	4.5 min
Poelenburg	Separated cycling lane	-0.06	0.16	-0.22	2.0 min
Linker Rottekade	Cycling suggestion lane	-0.32	-0.1	-0.22	2.0 min
Piekstraat	Cycling suggestion lane (lines only)	-0.81	-0.95	0.14	-1.3 min

Table 7.6: Comparison of Renovation Impacts on Cycling Infrastructure

The cv-dcm identifies differences in perceived cycling experience when infrastructure is improved, demonstrating its capability to assess cyclists' preferences. In contrast, Section 7.4.5 found no relationship between infrastructure characteristics and utility scores. This highlights the importance of controlling for the built environment when analysing the impact of cycling infrastructure characteristics.

This model is a valuable tool for the municipality to evaluate the impact of cycling infrastructure renovations. Furthermore, the cv-dcm could be applied to help with decision-making regarding the renovation of cycling infrastructure. For instance, if a road is found to be not attractive for cyclists and the municipality want to improve its cycling infrastructure, artificial intelligence could be used to generate a range of potential future designs. These designs could then be evaluated by the cv-dcm to determine perceived cycling experience. This, in turn, provides the opportunity to make trade-offs between cost and cycling environment when considering improvements to cycling infrastructure.

7.5. Cycling environment attributes model (Model 4)

Several models were proposed to predict cycling route choices, as shown in Table 7.3. The details of the cv-dcm model were provided in the previous chapter. The cycling environment attributes model (Model 4) is analysed in this chapter. This model is estimated to identify the cycling environment attributes that influence cycling route choices. It is particularly useful because this model allows to isolate the impact of each attribute on the cyclist's choice. So now clear insights into which attributes are most influential can be gained. As previously stated in Chapter 6 the environment attributes were matched with the images. Table 6.1 illustrates the manner and distance at which this was done. The majority of attributes have two levels: absent within a certain distance and present within a certain distance. Only trees posses an ordinal scale, ranging from 0 (no trees) to 4 (many trees).

Table 7.3 shows that most parameters have p-values below 0.05 indicating that the parameters are significant at 5% level. The rho-square indicates that this model has a slightly lower predictive performance compared to the cv-dcm, though the difference is relatively minor. Figure 7.27 illustrates the impact of the significant attributes on the utility. The number of trees has been averaged to align with the other binary elements. It can be observed that the presence of a separated cycling lane, trees, grass, water, and sun have a positive influence on cycle route choice, whereas the presence of car parking, clinkers (instead of asphalt), a tram on the road, houses, and industrial areas have a negative influence. These findings align with the literature and the cv-dcm. It highlights the significant influence of the built environment and cycling infrastructure type on cyclists' route preferences. Green, scenic surroundings and separated cycling infrastructure are strongly associated with greater cyclist preference for routes, while urban features negatively impact route choice. This highlights the necessity for policy to prioritise green and separated cycling lanes, with the aim of encouraging cycling and enhancing the overall experience.

It can be observed that the utility value increases by 0.38 when a separated cycling lane is present. This environment variable exerts the greatest positive influence on cycling route choice. The beta parameter for travel time is -0.23. This indicates that, on average, cyclists are willing to detour by 1.5 minutes for a separated cycling lane on an 11-minute trip.

Furthermore, Figure 5.1 shows that industrial areas are perceived as particularly unpleasant for cycling, with a disutility score of 0.62. This is likely due to a combination of factors, including the lack of aesthetic appeal and the prevalence of trucks in these areas (Pokorny and Pitera, 2019). As the cv-dcm also showed, cyclists find it particularly unpleasant to cycle past moving trucks, which is common in industrial areas. Therefore, it is not surprising that industrial areas have such a low utility score.

It is notable that the built environment exerts a considerable influence on cycling route choice behaviour. The analysis of the data demonstrated that colour and width, for instance, were not significant parameters. Although it is also possible that the data is not entirely accurate for width and colour. Consequently, this study emphasises the pivotal role of the built environment on cycling route choice, suggesting that it is more influential than the characteristics of cycling infrastructure. From a policy perspective, it is therefore recommended that urban environments incorporate greenery, such as trees, grass and water.

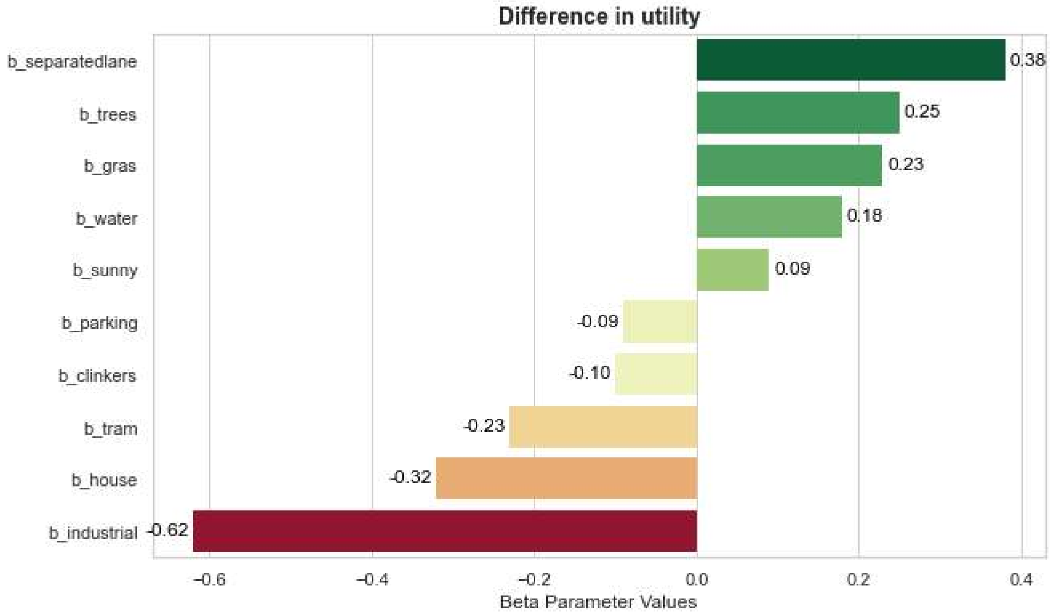


Figure 7.27: Difference in utility (based on Model 4 in Table 7.3)

The plant and cycling suggestion lane parameters are not statistically significant as can be seen in Table 7.3. Accordingly, they were excluded from further analysis. Cycling suggestion lanes are often found on narrow urban roads with high traffic volumes, which may explain their insignificance. As evidenced by the cv-dcm, the presence of a cycling suggestion lane has a slightly more positive influence compared to a normal road on cycling route choice. To address this, it is recommended to extend the model with additional elements that could explain busy environments, such as population density or car intensity. This was considered, but due to time constraints, an extensive analysis was not conducted. Alternatively, it is possible that cycling suggestion lanes have minimal influence on route choice, regardless of other environmental factors.

In addition, plants are not significant. This is in contrast to expectations based on previous research, which suggested that plants would influence route choice. The insignificancy is likely due to the method of data collection. The BGT only includes information on plants located in public spaces. Consequently, plants in residents' front gardens are not included. This results in a significant portion of plants being absent from the model, contributing to the insignificance. Additionally, the binary classification of whether an attribute is present or absent is somewhat rough. If more time had been available, a more precise approach to aligning the data with image details could have been explored.

Furthermore, the standard error of the parameter for the tram is notably high. This is likely due to the fact that there are not that many images with a tram on the road and the fact that it is highly unpleasant for cyclists when the tram is situated on the same road surface as used by cyclists. However, if the tram is situated a few metres away from the cycle path, then the impact is significantly reduced. The model does not account for this difference, resulting in a highly inconsistent effect of the tram across choice situations.

7.6. Latent class models

The previous models are MNL models, which assume that each individual has the same preference with regard to the cycling route. However, as Heinen et al. (2010) suggests, preferences can differ significantly across demographic groups. Inexperienced cyclists, women, and older adults place a greater value on traffic safety, while others are more inclined to choose the fastest route. To account for this heterogeneity, latent class (LC) models were applied to identify distinct subgroups of cyclists with similar preferences (Weller et al., 2020).

The estimation of latent class models involves the consideration of varying numbers of classes. Given that the likelihood of latent class choice models is not necessarily globally concave, 100 random starting values are generated. The optimal number of classes is then selected based on the BIC value. BIC considers both model fit and parsimony, and is therefore applied instead of the likelihood. Table 7.7 shows the estimation results. It can be observed that the BIC value is lowest for the LC model with five classes. The rho-square value demonstrates an increase of 0.1 in comparison to the MNL model, which is a notable difference.

Train set (N = 9135)	**MNL Model 3**	**Latent Class 2**	**Latent Class 3**	**Latent Class 4**	**Latent Class 5**	**Latent Class 6**
Number of Parameters	3	7	11	15	19	23
Log-Likelihood	-5590	-5219	-5128	-5063	-5021	-5008
p2	0.117	0.176	0.19	0.2	0.207	0.209
Cross-Entropy	0.612	0.571	0.561	0.554	0.550	0.548
BIC	11600	10502	10356	10262	10216	10226

Table 7.7: Model Comparison Results of Latent Class Models

7.6.1. Parameter estimates 5 class model

The latent class model comprising five classes was analysed. The estimated parameters and covariate are presented in Table 7.8. The covariate ”Age” is found to be significant for all classes. Both numeric and dummy-coded specifications for age were tested. Based on the BIC value, the numeric specification provided a better model fit. However, this approach may fail to capture potential non-linear effects of age on class membership.

Additional covariates demonstrating a high correlation with the importance attributes displayed in Figure 7.4 were also included. These were age, trip purpose and commuting days. Subsequent analyses also incorporated gender and income. However, only age was found to affect cycling route choice and consequently included in the model. This indicates that route preferences are not strongly influenced by demographics, aside from age. It is possible that other factors not included in the survey, such as personality, may be significant in understanding the choice of cycling routes.

	Class 1			**Class 2**			**Class 3**			**Class 4**			**Class 5**		
Name	Environment Enthusiasts			Balanced prioritisers			Traffic-Light Avoiders			Efficiency Seekers			Indifferent Cyclists		
Percentage	37%			26%			6%			12%			19%		
	est	**s.e.**	**p-val**	**est**	**s.e.**	**p-val**	**est**	**s.e.**	**p-val**	**est**	**s.e.**	**p-val**	**est**	**s.e.**	**p-val**
Parameters															
B_{tt}	0.02	0.035	0.57	-0.48	0.070	0.00	-0.51	0.140	0.00	-2.21	0.213	0.00	-0.05	0.030	0.12
B_{tl}	-0.19	0.044	0.00	-0.30	0.056	0.00	-2.56	0.345	0.00	-2.35	0.272	0.00	-0.04	0.055	0.49
B_{score}	2.33	0.191	0.00	1.70	0.145	0.00	0.81	0.295	0.01	1.17	0.443	0.01	0.22	0.183	0.23
Covariate															
Age	0.00	NA	NA	-0.51	0.126	0.00	-0.59	0.186	0.00	-0.80	0.140	0.00	-0.64	0.140	0.00

Table 7.8: 5 class model

The relative importance of each class is calculated, and a description is provided for each class.

7.6.2. Class descriptions

	Class 1	Class 2	Class 3	Class 4
Name	Environment Enthusiasts	Balanced Prioritisers	Traffic-Light Avoiders	Efficiency Seekers
Percentage	37%	26%	6%	12%
Relative Importance (%)				
Travel Time	-	34%	29%	64%
Traffic Lights	5%	7%	48%	22%
Environment	95%	59%	23%	16%

Table 7.9: Relative Importance and Model Performance Comparison

Class 1: Cycling Environment Enthusiasts (37%)

This is the largest class, comprising 37% of respondents. This group prioritises the cycling environment above all else as the relative importance is 95%. Travel time is not even a consideration for this group, as B_{tt} is not statistically significant. Traffic lights have a minimal influence on their decision-making process. Older cyclists are more likely to belong to this class, indicating that older cyclists attach greater importance to the cycling environment than younger cyclists.

Class 2: Balanced Prioritisers (26%)

This group represents 26% of respondents and demonstrates a more balanced distribution of priorities across travel time, traffic lights, and the environment. For this group, the environment is the most significant factor (59%), followed by travel time (34%), and then traffic lights (7%). This group reflects individuals who weigh all aspects of a route carefully, making trade-offs between efficiency and environment.

Class 3: Traffic-Light Avoiders (6%)

Traffic-Light Avoiders is the smallest class. This group demonstrate strong preferences for avoiding traffic lights, which account for 48% of their relative importance. Travel time (29%) and the environment (23%) are secondary considerations. Their aversion to traffic lights emphasises the need for uninterrupted cycling routes.

Class 4: Efficiency Seekers (12%)

Efficiency Seekers focus mostly on minimising travel time, which is the most significant factor for this group (64%). Traffic lights (22%) and the environment (16%) are far less important. This group consists mainly of younger individuals, indicating that younger cyclists prioritise minimising travel time more than older cyclists. The municipality could emphasise direct, fast cycling routes with minimal delays.

Class 5: Indifferent Cyclists (19%)

This group is somewhat odd, as none of the parameters are statistically significant for their cycling route choices. This lack of clear preferences might indicate that these respondents did not engage seriously with the stated choice experiment or that their decisions are influenced by unobserved factors not captured in the model. At 19%, this class represents a notable portion of respondents, highlighting the need for investigation in further research into the reasons for their indifference.

From a policy perspective, these finding suggests that age-specific interventions may be more effective than generalised approaches. Older cyclists may benefit from routes with separated cycling lanes and scenic elements. In contrast, younger cyclists may prefer direct, fast routes that prioritise efficiency. To illustrate, in neighbourhoods with a higher proportion of older residents, it is important to ensure the presence of separated cycling lanes and greenery that provide access to destinations such as local supermarkets, general practitioner offices, and town centres. By considering the specific needs of different age groups, policymakers can create a cycling network that aligns with these variety in preferences.

8
Conclusion, discussion and recommendations

In this Chapter, the conclusions will be presented, along with a discussion of research findings and recommendations for future work.

8.1. Conclusion

The conclusion presents the scientific contributions and addresses the research questions posed by the study.

8.1.1. Scientific contributions

This research contributes to the field of processing images into discrete choice models, where images are analysed using computer vision techniques. The relatively new model proposed by Cranenburgh and Garrido-Valenzuela (2023), known as cv-dcm, has been applied to understand cycling route choice behaviour. This model is capable of predicting choice behaviour based on both numerical attributes and images.

Notably, this is the first study that investigates cycling route choice behaviour using a large dataset of 6,500 unique street-level images in the stated choice experiment. The cv-dcm effectively predicts cycling route choice preferences, providing novel insights into the impact of cycling environments on decision-making. This approach provides a more realistic choice context compared to the majority of the current research, which relies on generated images or text-based descriptions.

This study builds on the prior cv-dcm application of Cranenburgh and Garrido-Valenzuela (2023) by introducing three key innovations: the pre-experiment image analysis, the use of an efficient design and a comprehensive data collection. The pre-experiment image analysis ensured that all characteristics of different cycling environments were visible in the images. Consequently, the model was able to effectively predict all different cycling environments. Furthermore, the image analysis facilitated the establishment of a ranking of the images, allowing for the utilisation of an efficient design, which is typically more advantageous than other designs. This approach improves trade-off insights and reduces parameter standard errors. The combination of an efficient design with a substantial quantity of real images for the prediction of choice behaviour represents a novel approach.

The cv-dcm relies on a neural network, which can make interpretability challenging. This study has addressed this by conducting a comprehensive data collection to represent the cycling environment with interpretable parameters. This allowed for a detailed examination of parameter influences on predicted utility scores of the cv-dcm and facilitated cycling route choice estimations using a traditional discrete choice model. This analysis has facilitated a clearer understanding of the influence of interpretable attributes on cycling route choice and the cycling environment score of the cv-dcm, bridging the gap between neural network models and classical DCMs.

The findings reveal valuable insights into how cyclists perceive and experience different cycling environments and infrastructure. These insights not only contribute to scientific knowledge but also have practical implications making this research particularly beneficial to policy makers.

8.1.2. Addressing the research questions

The following main research question is answered in the study:

“How does the cycling environment influence cycling route choice behaviour?”

This research question is addressed through five sub-questions, each contributing to the answer of the main research question. The following conclusions were drawn from these questions:

Q1:”What trade-offs do individuals make regarding cycling route choice?”

An extensive literature review was conducted in order to identify the most significant factors. The most significant factors were employed in this study: travel time, traffic lights and environment. Previous studies have also investigated this with a stated choice experiment, but this has not been done with real images before. Subsequently, the impact of these three variables on cycling route choice was evaluated. The respondents were asked to indicate how important these factors were in the decision making of choosing a cycling route, by rating each on a scale of 1 to 10. The results demonstrated that respondents perceived the environment to be the most important factor (7.6), followed by travel time (6.1) and traffic lights (5.5). Several discrete choice models were developed to predict cycling route choice behaviour. These findings supports the aforementioned ranking, indicating that the environment is approximately three times more important than travel time based on scaled maximum utility differences. Additionally, travel time is deemed more important than the number of traffic lights. In conclusion, these findings highlight the crucial role of the environment in choosing cycling routes.

Q2: ”What face validity conclusions can be drawn from the decision behaviour of the cv-dcm?”

The first research question revealed that the cycling environment is perceived as a highly influential factor in choosing a cycling route. This was investigated by applying the cv-dcm and the cycling environment attributes model to predict behaviour. The explained variance of the cv-dcm is higher than that of the other models that do not include images to explain cycling route choice. So the research has shown that the cv-dcm is capable of capturing attributes embedded in images to explain cycling route choice.

The cv-dcm assigns a predicted cycling environment utility score to each image. The reason behind the assignment of a particular score to an image is not immediately clear, given that it is based on a deep neural network. Therefore it was analysed how the model predicts and whether this aligned with expected human decision-making in cycling route choice.

The visual analysis has revealed that there is a relationship between the predicted cycling environment utility scores and the level of greenery, buildings and cycling infrastructure. Green, open environments with dedicated cycling infrastructure are valued higher, while more crowded, urban areas with normal roads are perceived as less desirable for cycling. The spatial analysis has provided a map representation of the cycling environment scores. The analysis showed insights where cyclists have a preference for cycling and where they do not. low density areas have more attractive cycling environments than high density areas.

Q3: "How does the cycling environment influence the decision behaviour of the cv-dcm?"

Now that it has become clear that the cv-dcm can accurately predict cycling infrastructure and the built environment, a series of quantitative analyses have been conducted to examine how different cycling infrastructure and the built environment are experienced by cyclists. The findings of these analyses highlight that cyclists prefer separated cycling lanes over normal roads and cycling suggestion lanes, with suggestion lanes scoring slightly higher than normal roads. Moreover, recreational areas are assigned high utility scores, whereas industrial areas and residential areas are assigned low utility scores.

It was investigated whether characteristics, such as width, colour and pavement of cycling infrastructure types influenced cycling experience. The analyses demonstrated that there was minimal correlation between these characteristics and the cycling experience. This could indicate that maintaining a consistent built environment is essential for accurately scoring these characteristics. A further analysis was conducted in which the built environment was maintained with minimal variation. In contrast, these analyses showed that the cv-dcm identified a difference in perceived cycling experience when cycling infrastructure has been improved, which indicates that the cv-dcm is capable of accurately estimating differences in characteristics, such as width, colour and pavement. As a result, this model represents a valuable tool for the municipality to evaluate the impact of cycling infrastructure renovations.

Q4: "How do cycling environment attributes influence cycling route choice behaviour?"

A model was developed to estimate cycling route choice using cycling environment attributes instead of images. It is particularly useful because this model allows to isolate the impact of each attribute on the cyclist's choice. Clear insights into which attributes are most influential were gained, which can not be done easily with the cv-dcm. The research showed that this model predicts slightly less well than the cv-dcm, namely a minimal difference in rho-square of 0.009. The findings showed that the presence of a separated cycling lane, trees, grass, water, and sun have a positive influence on cycle route choice, whereas the presence of car parking, clinkers (instead of asphalt), a tram on the road, houses, and industrial areas have a negative influence. It highlights that, on average, individuals are willing to take a detour of 1.5 minutes to cycle on a separated cycling lane instead of a normal road. These results also highlight the significant role of the built environment in shaping cycling route preferences.

Q5: "How do different demographic groups (e.g., age, gender) prioritise attributes when choosing cycling routes?"

A latent class model was applied to identify the different demographic groups. It was revealed that older cyclists attach greater importance to the cycling environment than younger cyclists. By contrast younger cyclists prioritise travel time more than older cyclists. Age was found the only significant covariate. It was observed that approximately one-third of respondents indicated that their choice in cycling route was almost only influenced by the cycling environment. For 12% of respondents, travel time was the most important factor, while 6% indicated that traffic lights were the primary consideration. These groups are smaller than expected, indicating that cycling environments are of significant importance to many individuals. Additionally, a considerable proportion of 19% demonstrated indifference towards all attributes, suggesting that a portion of respondents may not have answered the stated choice experiment in a serious manner.

After addressing all sub-questions, the main research question—"How does the cycling environment influence cycling route choice behaviour?"—can now be answered. This research has demonstrated that the cycling environment is the most significant factor influencing route choice, more than other travel time and traffic lights. Cyclists exhibit clear preferences for well-designed, visually appealing environments, emphasising the importance of integrating these attributes into the design of cycling environments. By understanding the attributes that cyclists value, this study can assist policymakers in designing environments that promote cycling.

8.2. Discussion

The goal of the study was to explore the preferences of various groups on cycling route choice. And to analyse the influence of cycling environment attributes on individuals' preferences. After extensive research, these goals were answered as described in the conclusion. The process that led to these conclusions included assumptions, methods and estimates that are worth discussing. This section critically discusses these uncertainties and the results that have been presented throughout the report.

8.2.1. Limitations of the stated choice experiment

The findings of this study indicate that the cycling environment is of great importance. Previous research has frequently concluded that for commuting purposes, travel time is the most important factor. However, this study has identified that the environment is three times more important than travel time. The importance of the environment may also be attributed to the manner in which the data was presented to respondents. The environment was displayed through images, whereas travel time and traffic lights were represented as numeric attributes. Research has demonstrated that images are more effective at capturing attention than numeric attributes (Murwirapachena and Dikgang, 2022). Consequently, respondents are more likely to select the more favourable image than to consider the numeric attributes. However, this does not necessarily corresponds to actual behaviour. Consequently, the importance of environment may be slightly overestimated.

In order to isolate the specific effect of travel time, it was assumed that the presence of traffic lights did not contribute to additional travel time. Had traffic lights been assumed to add extra travel time, it would have been challenging to isolate the influence of travel time from that of traffic lights. By maintaining these attributes as independent variables, the model was able to separately estimate the parameters for travel time and traffic lights. However, it is possible that the impact of traffic lights on cycling route choice has been slightly underestimated, given that they do, in fact, have the potential to increase travel time.

An actual cycle route is comprised of numerous segments, each with different characteristics that collectively influence the cycling experience. In the study, to maintain simplicity for respondents, one image was selected per cycle route. A single image may not fully capture real-world cycling routes, potentially limiting the realism of the choice situations.

The rho-square of the models are relatively low in comparison to other discrete choice models. The latent class analysis revealed that for 20 percent of the respondents, all parameters were insignificant. This may suggest that the stated choice experiment was sometimes answered in a non-serious manner, with respondents clicking through without fully engaging with the questions.

One of the limitations of stated choice experiments is the potential differences between individuals' stated preferences and their actual preferences (Wardman, 1988). Respondents may overestimate or underestimate certain preferences. For instance, respondents are not expected to cycle the given route, which may result in an underestimation of the travel time. Combining revealed and stated preference data can provide a more comprehensive understanding of decision-making and help validate the findings of stated choice experiments.

8.2.2. Limitations of the street-level image collection

Each segment was represented by one single image. In the case of an image featuring a van, the segment was assigned a lower score. This is not necessarily due to the cycling infrastructure or built environment, but rather the presence of traffic. The same can be said for the weather. Despite the recommendation in the survey to exclude weather from the decision-making process, it is a significant element in the cycling environment attributes model. These factors has significant impacts on the assessment of cycling environments. The inclusion of multiple images per segment reduces the impact of these factors on the rating of the segments.

The images were captured between late February and early April. As evidenced in the images, trees are leafless and plants are not in bloom. It is plausible that trees and plants in summer could contribute to a higher preference of the environment compared to the trees visible during winter.

The images reveal a minimal presence of cyclists, even on roads that experience high traffic volumes during the day. The analyses indicated that width has a minimal impact on the utility score. The study of Greibe and Buch (2015) demonstrated that cyclists prioritise width more when intensity is high. If there were many other cyclists, it is plausible that the width would have been a significant factor. Consequently, the lack of cyclists in the images likely affected the results.

8.2.3. Limitations of the cycling environment data collection

Cycling environment attributes are matched with the images mostly with a binary classifier. This may be somewhat rough, which could result in less precise predictions. Additionally, the BGT only includes information located in public spaces. Consequently, some attributes are not included, such as plants in residents' front gardens. This results in a significant portion of plants being absent from the model. For trees it is counted how many trees there are on a segment. However the difference in segment length introduces a degree of inaccuracy into this method.

8.2.4. Limitations of the cycling environment attributes model

The relatively low rho square for the cycling environment infrastructure model may be attributed to the presence of a larger error variance in the images compared to numerical attributes. It is possible that the model does not fully account for certain elements present in the image, such as construction work, temporary obstacles, or vehicles driving past. Additionally, the model does not incorporate interaction effects, which could potentially impact the accuracy of the predictions. For example, an interaction effect between road type and car intensity may be observed. In a residential area, the impact of road sharing with cars may be less significant than in a busy neighbourhood access road. Additionally, the utility of travel time and traffic lights is estimated in a linear manner, whereas the relationship may not be linear. It is possible that as travel time increases, the disutility derived from it also increases.

The plant and cycling suggestion lane parameter are not statistically significant in this model. The reason that cycling suggestion lane is probably not significant is that such lanes are often observed on narrow urban roads with high traffic volumes. It is recommended to extend the model with additional elements that could explain busy environments, such as population density or car intensity. In addition, plants are not significant. The insignificancy is likely due to the method of data collection.

8.2.5. Limitations of the cv-dcm

The cv-dcm scores are not explained easily by interpretable parameters. Unlike traditional discrete choice models, where parameters provide clear and quantifiable insights into decision-making, the cv-dcm relies on features extracted from images through a deep neural network. This limits the model's applicability for the municipality who require transparent and actionable insights.

Additionally, there are reasons why the explained variance for the cv-dcm is relatively low. It is more difficult to give precise reasons, as the cv-dcm score is not easily explainable to humans. But it can be observed that when a van or truck was present in the image, the cv-dcm assigned a significantly lower score. It can be argued that the presence of such vehicles is a relevant factor for cyclists, but it also depends on whether they are driving or parked. The experience of cycling past moving vehicles is often perceived as unpleasant due to concerns about road safety and noise, whereas the impact of parked vehicles may be less pronounced. It can be suggested that the cv-dcm may not fully capture the nuances in these preferences that are evident to humans. It was also observed that the cv-dcm may encounter difficulties in predicting tram lines. This attribute is relatively straightforward for humans to understand, such as the annoyance caused by a tram on a cycling lane. However, they are more complex for the cv-dcm due to the limited visual information available, with tram lines representing a relatively minor aspect of the image.

8.3. Recommendations

From this research, there are several aspects that can be further explored to further the knowledge of the working of the cv-dcm and to further the knowledge of cycling routes. This section describes these aspects.

8.3.1. Analysing perceptions

The survey included questions regarding the respondents' perceptions of the image, in terms of its traffic safety, social safety and beauty. It would be valuable to analyse whether these perceptions have an influence on route selection, and to what extent. Furthermore, it would be beneficial to examine which attributes of the cycling environment are most important for ensuring traffic safety or social safety. For instance, it can be assumed that lighting and the presence of houses contribute to social safety, while the type of cycling lane to traffic safety. However, it should be noted that all images were taken in daylight, which may have influenced the perception of social safety.

8.3.2. Improving reliability with multiple images

As previously discussed, one image was included per segment. Objects such as vans or other temporary road obstacles are visible in images. It would be beneficial to include multiple images per segment in subsequent studies which would help to ensure that the segment score is less affected by the presence of such attributes.

8.3.3. Analysing revealed preferences

This study applied a stated choice experiment. To validate whether cyclists prioritise the environment to the same extent in real-world scenarios, it would be valuable to compare this research with revealed preference. One potential method is to analyse Strava or GPS data, which captures actual cycling routes and behaviour. By examining how cyclists navigate through a city using revealed preferences, it could be explored whether environmental factors such as greenery, separated cycling lanes, and road quality significantly influence route choices in reality. In addition, this model could be extended to cycling routes. By connecting segments and observing the choices made by individuals according to the model, it is possible to compare these choices with actual cycling routes.

8.3.4. Explainable AI

It would be valuable to explore the use of machine learning models to analyse the factors influencing individual cycling environment scores. Techniques such as SHAP (Shapley Values) or LIME (Local Interpretable Model-Agnostic Explanations) could provide insights into which attributes, such as lane width, greenery, or parked cars, have the greatest impact on each specific score. This approach could reveal localised priorities. Further research into this method could help identify targeted interventions to improve low-scoring areas.

In the field of computer vision, there is considerable scope for further research. For instance, the master's thesis by Bakker (2024) explored whether explainable artificial intelligence (XAI) techniques could improve the interpretability of the cv-dcm. Using LIME, the study analysed individual images to determine whether the model could identify features responsible for high or low scores. The findings indicated that this was challenging with the applied methodology. However, combining LIME with object detection could improve interpretability, enabling a clearer understanding of how specific features within an image contribute to the score, rather than relying solely on underlying data.

8.3.5. Panoptic segmentation, non-linear effects, interaction effects

To improve the Cycling Environment Attributes Model, future research could refine the data linking process, moving beyond binary classification to approaches like GIS-based rectangles to calculate proportions of elements (e.g., buildings, grass, water). Integrating panoptic segmentation could further improve accuracy by detecting hard-to-collect features like cars or construction work directly from images. Additional attributes, such as cycling infrastructure characteristics, population density, interaction effects, as well as non-linear factors like travel time disutility, would also improve the model.

8.3.6. Heterogeneity

A latent class model was constructed that incorporated the predicted cycling environment score. The impact of attributes shown in the image on different demographic groups was not investigated. Some groups may prioritise the cycling infrastructure, whereas other groups may attach greater importance to greenery. Additionally, covariates such as age could be incorporated into the training of the cv-dcm. For example, it would be interesting to analyse whether the predicted utility score for a given image differs between older and younger people. It may be that older people place a higher value on a green environment, while younger people also like cycling through an urban setting.

8.3.7. AI-driven image editing models

The potential to apply the cv-dcm model in the formulation of policy, rather than in its evaluation, represents another avenue for further research. For instance, if a road is found to be not attractive for cyclists and the municipality want to improve its cycling infrastructure, ai-driven image editing models could be used to generate a range of potential future designs. These designs could then be evaluated by the cv-dcm to determine perceived cycling experience. This, in turn, provides the opportunity to make trade-offs between cost and cycling environment when considering improvements to cycling infrastructure.

8.3.8. Video and virtual reality in choice modelling

The majority of current research on choice models is based on text-based descriptions. The cv-dcm represents a significant advancement in choice modelling, as it is the first model that incorporates images into choice situations, thereby expanding the scope of choice modelling. To further improve the realism of the model, it is recommended to incorporate multiple images or videos which simulate the dynamic nature of cycling routes. The potential of virtual reality could also be explored, allowing participants to experience routes in a more realistic manner. Additionally, sensory factors such as noise and smell could be integrated to capture the full experience. This approach enables participants to make choices in a highly realistic environment, offering deeper insights into how factors such as greenery, traffic noise, and cycling infrastructure influence route preferences. To the best of my knowledge, there are currently no choice models that integrate video images or virtual reality into choice situations.

8.3.9. Applicability to other cities

The findings of this research could be replicated to other cities, provided that the necessary data is available. It is necessary to obtain street-level images for this purpose. Google has a substantial repository of Google Street View images for each country; however, there is a notable absence of images captured directly from the cycling lane. This is an essential component for the replication of this research. Furthermore, with regard to copyright and usage rights, it is not the intention to download thousands of Google Street View images (Helbich et al., 2024). A considerable number of large municipalities in the Netherlands have established their own databases comprising street-level images, including those of cycling lanes (Gemeente Amsterdam, 2024). Furthermore, data of the cycling network is required. This is available for the majority of Dutch cities. OSM data could also be employed. With this information, the same methodology as in this study could be applied.

To assess the cycling network in other cities in the Netherlands, no model needs to be trained as this has already been done in this study. While this methodology could also be applied in other countries, city layouts and cycling infrastructure may differ significantly. As such, the applicability of this trained cv-dcm outside the Netherlands may be limited. It may be necessary to train a new cv-dcm model following the same method as applied in this study. The utilisation of survey platforms is currently challenging when there are thousands of images incorporated into the survey. Consequently, a website for the survey has been developed. However, this may present certain complexities due to the necessity of programming expertise for the website design.

8.3.10. Cv-dcm for other studies

The incorporation of images in stated choice experiments may prove beneficial for the prediction of choice behaviour in other domains where textual data alone is insufficient. Two domains are highlighted in this paragraph, but there are obviously many more.

One such domain is the assessment of crowdedness in public transport. Crowdedness is inherently visual. Describing crowd density with text (e.g., ”very crowded”) lacks specificity, while images provide a much clearer understanding of the environment. By incorporating images of crowded public transport spaces, researchers can better understand how individuals choose routes, times, modes, or locations to avoid crowds. This could be useful for studies on public transport, but also people movement in busy urban areas or festivals.

To remain within the field of cycling, future research could investigate how the environment influences transport mode choice. This would involve analysing whether the environment, such as greenery and cycling infrastructure, affect individuals’ decisions to choose a bicycle over a car.

8.4. Relevant policy insights

One of the aims of the research was to inform the municipality of Rotterdam about effective strategies for designing cycling environments that meet the preferences of cyclists. Accordingly, this section is provided which outlines the potential for this research to inform relevant policy insights for the municipality.

8.4.1. Measuring cycling experience

As previously stated in the introduction, the current methodology for measuring cycling experience is based on surveys and interviews. These methods have significant drawbacks; they are often time-consuming, costly, and provide only a limited perspective, as they only reflect the opinions of a small group of individuals. Currently it has been challenging to measure cycling experience in a quantitative way. The cv-dcm model offers a solution to these limitations by providing a more applicable and scalable quantitative method for measuring cycling experience.

8.4.2. Evaluating infrastructure improvements

Currently, when improvements are made to the cycling infrastructure, such as the Walenburgerweg, no evaluations are conducted. This model introduces a quantitative and systematic way to evaluate the effectiveness of cycling improvements on perceived cycling experience. As demonstrated in Chapter 7.4.6, this model enables a direct comparison of the cycling experience before and after infrastructure improvements.

The model allows for the expression of utility differences in measurable terms, such as time. It enables cyclists’ willingness to take a detour on new infrastructure. This information can be translated into monetary terms using value-of-time calculations, providing a robust framework for evaluating the benefits and costs of cycling infrastructure improvements. These insights are not only valuable for the assessment of infrastructure improvements, but also can serve as input for future decision-making processes.

8.4.3. Relative importance of attributes

Currently, origin-destination matrices for cycling routes in traffic models are estimated using a split of 50% fastest routes and 50% shortest routes. However, the findings of this study highlight the substantial impact of the cycling environment on route choice. Therefore, incorporating the best cycling environment route into traffic models would improve their accuracy.

It is recommended to compare this model to actual cycling routes. There may be a difference between stated and revealed preferences. If validated, incorporating best cycling environments routes into traffic models would provide more realistic and effective predictions.

8.4.4. Cycling infrastructure

The analysis of the impact of cycling infrastructure type on the predicted utility cycling score revealed that the value placed on separated cycling lanes is significantly higher than that attributed to cycling suggestion lanes. The analysis in Section 7.4.4 demonstrated that the average cyclist is willing to make a 1.5 minute detour to cycle on a separate cycling lane rather than a cycling suggestion lane for a cycle trip of approximately 11 minutes. Therefore, it is strongly recommended to construct separated cycling lanes on busy neighbourhood access roads.

8.4.5. Built environment

The findings of the analysis indicated that the surrounding environment has a considerable influence on the selection of cycling routes. The presence of natural elements, including grass, water, and trees, was identified as a positive factor. Consequently, it is recommended that urban planners consider incorporating greenery, also in very urban densely populated areas.

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References

Akoglu, Haldun (2018). "User's Guide to Correlation Coefficients". In: *Turkish Journal of Emergency Medicine* 18.3, pp. 91–93. ISSN: 2452-2473. DOI: https://doi.org/10.1016/j.tjem.2018.08.001. URL: https://www.sciencedirect.com/science/article/pii/S2452247318302164.

Bakker, B.J. (2024). "Leveraging LIME for Human-Understandable Explanations in Urban Computer Vision Models". MA thesis. Delft University of Technology. URL: http://resolver.tudelft.nl/uuid:6cfbd82f-dd12-4593-87e2-83726053dbfc.

Bernardi, Silvia et al. (Oct. 2018). "Modelling route choice of Dutch cyclists using smartphone data". In: *Journal of Transport and Land Use* 11.1. DOI: 10.5198/jtlu.2018.1143. URL: https://www.jtlu.org/index.php/jtlu/article/view/1143.

Berry, William D (1985). *Multiple Regression in Practice*. Sage.

BGT (2024). *Basisregistratie Grootschalige Topografie*. URL: https://www.kadaster.nl/zakelijk/registraties/basisregistraties/bgt.

Bohle (2000). "Attractiveness of bicycle-facilities for the users and evaluation of measures for the cycle-traffic". In: *VeloMondial Conference*.

Bouwgrondstoffen, De Hoop (May 2024). *Waarom zijn fietspaden in Nederland rood? Het verhaal van Tilrood*. Accessed: 2024-12-09. URL: https://www.dehoop-bouwgrondstoffen.nl/over-de-hoop/nieuws/waarom-zijn-fietspaden-in-nederland-rood-het-verhaal-van-tilrood.

CBS (2024a). *CBS*. URL: https://opendata.cbs.nl/statline/#/CBS/nl/.

— (2024b). *Statistieken gemeente Rotterdam*. URL: https://allecijfers.nl/toelichting/migratie/.

— (2024c). *Statistieken woonplaats Rotterdam*. URL: https://allecijfers.nl/woonplaats/rotterdam/.

Chen, J. et al. (2013). "Research on Geographical Environment Unit Division Based on the Method of Natural Breaks (Jenks)". In: *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences* XL-4/W3, pp. 47–50. DOI: 10.5194/isprsarchives-XL-4-W3-47-2013. URL: https://isprs-archives.copernicus.org/articles/XL-4-W3/47/2013/.

Chen, Peng et al. (2018). "A GPS data-based analysis of built environment influences on bicyclist route preferences". In: *International Journal of Sustainable Transportation* 12.3, pp. 218–231. DOI: 10.1080/15568318.2017.1349222. URL: https://doi.org/10.1080/15568318.2017.1349222.

ChoiceMetrics (2024). *Ngene*. URL: https://choice-metrics.com/download.html.

Cint (2024). *Cint*. URL: https://www.cint.com/.

Columbiauniversity (2020). *Discrete Choice Model and Analysis*. URL: https://www.publichealth.columbia.edu/research/population-health-methods/discrete-choice-model-and-analysis.

Cranenburgh, Sander and Francisco Garrido-Valenzuela (Aug. 2023). "Computer vision-enriched discrete choice models, with an application to residential location choice". In.

Cranenburgh, Sander van (2024). *Staff Profile: S. van Cranenburgh, TU Delft*. URL: https://www.tudelft.nl/staff/s.vancranenburgh/?cHash=0b1102c6a8de488000dd4cd02794b2a3.

CROW (2024). *Kennisplatform CROW*. URL: https://www.crow.nl/.

Cyclomedia (2023). *Panoramafoto's Rotterdam Actueel*. URL: https://www.gis.rotterdam.nl/gisweb2/default.aspx.

Dane, Gamze et al. (2020). "Route Choice Decisions of E-bike Users: Analysis of GPS Tracking Data in the Netherlands". In: *Geospatial Technologies for Local and Regional Development*. Ed. by Phaedon Kyriakidis et al. Cham: Springer International Publishing, pp. 109–124. ISBN: 978-3-030-14745-7.

DataCamp (2024). *Cross-Entropy Loss Function in Machine Learning*. URL: https://www.datacamp.com/tutorial/the-cross-entropy-loss-function-in-machine-learning.

Donath, Carolin et al. (2012). "Predictors of binge drinking in adolescents: ultimate and distal factors - a representative study". In: *BMC Public Health* 12.1, p. 263. ISSN: 1471-2458. DOI: 10.1186/1471-2458-12-263. URL: https://doi.org/10.1186/1471-2458-12-263.

DTVConsultants (2023). *Are Dutch Cycling Lanes Wide Enough to Accommodate All Cyclists?* Accessed: 2024-12-07. URL: https://dtvcapacitybuilding.com/blog/research-are-dutch-cycling-lanes-wide-enough-to-accommodate-all-cyclists/.

Dubey, Abhimanyu et al. (2016). "Deep Learning the City: Quantifying Urban Perception at a Global Scale". In: *Computer Vision – ECCV 2016*. Ed. by Bastian Leibe et al. Cham: Springer International Publishing, pp. 196–212. ISBN: 978-3-319-46448-0.

Durand, Anne et al. (2023). *Multiculturele diversiteit in mobiliteit*. URL: https://fietsberaad.nl/getmedia/10edb43c-663c-4a18-a1aa-b59acbaf4054/KiM-brochure-Multiculturele-diversiteit-in-mobiliteit_def.pdf.aspx.

Dutch Cycling Embassy (2018). *Dutch Cycling Vision*. URL: https://dutchcycling.nl/wp-content/uploads/2022/05/Dutch_Cycling_Vision_EN.pdf.

Elu, Aitzol et al. (2021). "Inferring spatial relations from textual descriptions of images". In: *CoRR* abs/2102.00997. arXiv: 2102.00997. URL: https://arxiv.org/abs/2102.00997.

Embassy, Dutch Cycling (2023). *CROW Updates Bike Lane Width Recommendations*. Accessed: 2024-12-07. URL: https://dutchcycling.nl/knowledge/blogs-by-experts/crow-updates-bike-lane-width-recommendations/.

European Union (2023). *The Importance of Active Mobility in the Face of Climate Change*. URL: https://www.euroclima.org/en/recent-events-urban/articles-and-interviews/1981-world-bike-day-the-importance-of-active-mobility-in-the-face-of-climate-change.

Fietsersbond (2020). *Data fietsersbond*. URL: https://www.fietsersbond.nl/.

— (2023). *Wow! 1.600 fietsongevallen per jaar in Rotterdam: 'Terwijl we er makkelijk veel kunnen voorkomen'*. URL: https://indebuurt.nl/rotterdam/nieuws/verkeer/wow-1-600-fietsongevallen-per-jaar-in-rotterdam-terwijl-we-er-makkelijk-veel-kunnen-voorkomen~283785/.

Garrido-Valenzuela, Francisco (2024). *Staff Profile: Francisco Garrido-Valenzuela, TU Delft*. Accessed: 2024-11-10. URL: https://www.tudelft.nl/en/staff/f.garridov/?cHash=9e453a8f8a6dcb0026be2a7f9f604398.

Gemeente Amsterdam (2024). *Kernregistratie Panoramabeelden*. Accessed: 2024-12-10. URL: https://data.amsterdam.nl/data/datasets/jTWyWaKHODSTKg/kernregistratie-panoramabeelden.

Gemeente Rotterdam (2019a). *Fietskoers 2025*. URL: https://www.rotterdam.nl/fietsstad.

— (2019b). *Veilig Op Pad*. URL: https://www.rotterdam.nl/veilig-op-pad.

— (2023). *Verkeersveiligheidsprikker*. URL: https://www.rotterdam.nl/verkeersveiligheidsprikker.

Gössling, Stefan and Sophia McRae (2022). "Subjectively safe cycling infrastructure: New insights for urban designs". In: *Journal of Transport Geography* 101, p. 103340. ISSN: 0966-6923. DOI: https://doi.org/10.1016/j.jtrangeo.2022.103340. URL: https://www.sciencedirect.com/science/article/pii/S0966692322000631.

Goudappel (2024). *Omnitrans*. URL: https://www.goudappel.nl/en/expertise/data-and-it-solutions/traffic-modelling-software-OmniTRANS-Expert.

Greibe, Poul and Thomas Buch (Sept. 2015). "Road User Behaviour on One-way Cycle Tracks of Different Widths". In.

Heinen, Eva et al. (2010). "Commuting by Bicycle: An Overview of the Literature". In: *Transport Reviews* 30.1, pp. 59–96. DOI: 10.1080/01441640903187001. URL: https://doi.org/10.1080/01441640903187001.

Helbich, Marco et al. (2024). *To use or not to use proprietary street view images in (health and place) research? That is the question*. arXiv: 2402.11504 [cs.CV]. URL: https://arxiv.org/abs/2402.11504.

I&W (2020). *Klimaatbeleid*. URL: https://www.rijksoverheid.nl/onderwerpen/klimaatverandering/klimaatbeleid.

ImageNet (2024). *ImageNet*. URL: https://image-net.org/index.php.

Ito, Koichi and Filip Biljecki (2021). "Assessing bikeability with street view imagery and computer vision". In: *Transportation Research Part C: Emerging Technologies* 132, p. 103371. ISSN: 0968-090X. DOI: https://doi.org/10.1016/j.trc.2021.103371. URL: https://www.sciencedirect.com/science/article/pii/S0968090X21003739.

Jestico, Ben et al. (2016). “Mapping ridership using crowdsourced cycling data”. In: *Journal of Transport Geography* 52, pp. 90–97. DOI: `https://doi.org/10.1016/j.jtrangeo.2016.03.006`. URL: `https://www.sciencedirect.com/science/article/pii/S0966692316301168`.

Juarez, Roberto Nacxit Ramirez et al. (2023). “Cyclists’ perception of streetscape and its influence on route choice: A pilot study with a mixed-methods approach”. In: *Transportation Research Part F: Traffic Psychology and Behaviour*. URL: `https://api.semanticscholar.org/CorpusID:265005257`.

Kaparias, I. et al. (2024). “Using an instrumented bicycle to explore the responses of cyclists to pavement characteristics and defects”. In: URL: `https://api.semanticscholar.org/CorpusID:274137543`.

Kaplan, S. and C. Prato (2015). “A spatial analysis of land use and network effects on frequency and severity of cyclist-motorist crashes in the Copenhagen region”. In: *Traffic Injury Prevention* 16.7, pp. 724–731.

Karlsen, Katrine and Aslak Fyhri (2020). “Is Red the New Black? A Quasi-Experimental Study Comparing Perceptions of Differently Coloured Cycle Lanes”. In: *Frontiers in Psychology* 11. ISSN: 1664-1078. DOI: `10.3389/fpsyg.2020.554488`. URL: `https://www.frontiersin.org/journals/psychology/articles/10.3389/fpsyg.2020.554488`.

Kearney, Michael (Dec. 2017). “Cramér’s V”. In: DOI: `10.4135/9781483381411.n107`.

KiM (2023). *Mobiliteitsbeeld 2023*. URL: `https://www.kimnet.nl/publicaties/publicaties/2023/11/14/mobiliteitsbeeld-2023`.

Liu, Yanan et al. (2021). “Differences in street-scale built environment preferences towards biking: a latent class analysis of stated choice data”. In: *International Journal of Urban Sustainable Development* 13.3, pp. 706–714.

Ma, Xiangyuan et al. (2021). “Measuring human perceptions of streetscapes to better inform urban renewal: A perspective of scene semantic parsing”. In: *Cities* 110, p. 103086. ISSN: 0264-2751. DOI: `https://doi.org/10.1016/j.cities.2020.103086`. URL: `https://www.sciencedirect.com/science/article/pii/S0264275120314347`.

Mariel, Petr et al. (2021). *Environmental Valuation with Discrete Choice Experiments: Guidance on Design, Implementation and Data Analysis*. Cham: Springer. DOI: `10.1007/978-3-030-62669-3`. URL: `https://link.springer.com/book/10.1007/978-3-030-62669-3`.

McFadden, Daniel (1974). “The measurement of urban travel demand”. In: *Journal of Public Economics* 3.4, pp. 303–328. ISSN: 0047-2727. DOI: `https://doi.org/10.1016/0047-2727(74)90003-6`. URL: `https://www.sciencedirect.com/science/article/pii/0047272774900036`.

Misra, Aditi and Kari Watkins (2018). “Modeling Cyclist Route Choice using Revealed Preference Data: An Age and Gender Perspective”. In: *Transportation Research Record: Journal of the Transportation Research Board* 2672, p. 036119811879896. DOI: `10.1177/0361198118798968`.

Molin, Dr. Eric J.E. (2024). *SEN1221 Statistical Analysis of Choice Behaviour*. URL: `https://brightspace.tudelft.nl/d2l/le/content/597386/Home`.

Mouter, Niek et al. (2017). “An empirical assessment of Dutch citizens’ preferences for spatial equality in the context of a national transport investment plan”. In: *Journal of Transport Geography* 60, pp. 217–230. ISSN: 0966-6923. DOI: `https://doi.org/10.1016/j.jtrangeo.2017.03.011`. URL: `https://www.sciencedirect.com/science/article/pii/S0966692316307359`.

Muraina, Ismail (2022). “Ideal dataset splitting ratios in machine learning algorithms: general concerns for data scientists and data analysts”. In: *7th International Mardin Artuklu Scientific Research Conference*, pp. 496–504.

Murwirapachena, Genius and Johane Dikgang (2022). “The effects of presentation formats in choice experiments”. In: *Environmental Economics and Policy Studies* 24.3, pp. 421–445. ISSN: 1867-383X. DOI: `10.1007/s10018-021-00328-4`. URL: `https://doi.org/10.1007/s10018-021-00328-4`.

NDW (2024). *Nationaal Dataportaal Wegverkeer*. URL: `https://www.ndw.nu/`.

OpenStreetMap (2024). *OpenStreetMap Cycling network*. URL: `https://www.openstreetmap.org/#map=7/52.154/5.295`.

Pan, Xiaofeng et al. (2021). “Investigating tourist destination choice: Effect of destination image from social network members”. In: *Tourism Management* 83, p. 104217. ISSN: 0261-5177. DOI: `https://doi.org/10.1016/j.tourman.2020.104217`. URL: `https://www.sciencedirect.com/science/article/pii/S0261517720301436`.

Plotly (2024). *Data Apps for Production*. URL: https://plotly.com/.

Pokorny, Petr and Kelly Pitera (2019). "Truck-bicycle safety: an overview of methods of study, risk factors and research needs". In: *European Transport Research Review* 11.1, p. 29. ISSN: 1866-8887. DOI: 10.1186/s12544-019-0371-7. URL: https://doi.org/10.1186/s12544-019-0371-7.

Prato, C. (2009). "Route choice modeling: past, present and future research directions". In: *Journal of Choice Modelling* 2.1, pp. 65–100. DOI: https://doi.org/10.1016/S1755-5345(13)70005-8. URL: https://www.sciencedirect.com/science/article/pii/S1755534513700058.

QGIS (2023). *QGIS Geographic Information System*. QGIS Association. URL: https://www.qgis.org.

Ramírez, Tomás et al. (2021). "Measuring heterogeneous perception of urban space with massive data and machine learning: An application to safety". In: *Landscape and Urban Planning* 208, p. 104002. ISSN: 0169-2046. DOI: https://doi.org/10.1016/j.landurbplan.2020.104002. URL: https://www.sciencedirect.com/science/article/pii/S0169204620314869.

Rijkswaterstaat (2024). *MaxSpeedCar*. URL: https://downloads.rijkswaterstaatdata.nl/nwb-wegen/.

Rose, John M. and Michiel C. J. Bliemer (2009). "Constructing Efficient Stated Choice Experimental Designs". In: *Transport Reviews* 29.5, pp. 587–617. DOI: 10.1080/01441640902827623. eprint: https://doi.org/10.1080/01441640902827623. URL: https://doi.org/10.1080/01441640902827623.

Rossetti, Tomás, Angelo Guevara, et al. (2018). "Modeling safety as a perceptual latent variable to assess cycling infrastructure". In: *Transportation Research Part A: Policy and Practice* 111, pp. 252–265. ISSN: 0965-8564. DOI: https://doi.org/10.1016/j.tra.2018.03.019. URL: https://www.sciencedirect.com/science/article/pii/S0965856417309278.

Rossetti, Tomás, Hans Lobel, et al. (2019). "Explaining subjective perceptions of public spaces as a function of the built environment: A massive data approach". In: *Landscape and Urban Planning* 181, pp. 169–178. ISSN: 0169-2046. DOI: https://doi.org/10.1016/j.landurbplan.2018.09.020. URL: https://www.sciencedirect.com/science/article/pii/S0169204618310260.

Scott, Darren M et al. (2021). "Route choice of bike share users: Leveraging GPS data to derive choice sets". In: *Journal of Transport Geography* 90, p. 102903.

Sifringer, Brian et al. (2020). "Enhancing discrete choice models with representation learning". In: *Transportation Research Part B: Methodological* 140, pp. 236–261. ISSN: 0191-2615. DOI: https://doi.org/10.1016/j.trb.2020.08.006. URL: https://www.sciencedirect.com/science/article/pii/S0191261520303830.

Significance (2022). *Values of Time, Reliability and Comfort in the Netherlands 2022*. URL: https://english.kimnet.nl/publications/publications/2024/04/03/new-values-of-travel-time-reliability-and-comfort-in-the-netherlands.

Stewart, G. and G. McHale (2014). "The Effect of Cycle Lanes on Motorist Overtaking Behaviour". In: *Transport Research Part F: Traffic Psychology and Behaviour*. Accessed: 2024-12-07. URL: https://www.napier.ac.uk/~/media/worktribe/output-180554/stewartmchaletranrevisedpdf.pdf.

Ton, Danique et al. (2017). "How do people cycle in Amsterdam? Estimating cyclists' route choice determinants using GPS data from an urban area". In: *Transportation Research Record: Journal of the Transportation Research Board* 2662, pp. 1–10. DOI: 10.3141/2662-09.

Touvron, Hugo et al. (2021). *Training Data-efficient Image Transformers Distillation Through Attention*. arXiv: 2012.12877 [cs.CV]. URL: https://arxiv.org/abs/2012.12877.

Tran, Phuong T. M. et al. (2020). "Cyclists' personal exposure to traffic-related air pollution and its influence on bikeability". In: *Transportation Research Part D: Transport and Environment* 88, p. 102563. ISSN: 1361-9209. DOI: https://doi.org/10.1016/j.trd.2020.102563. URL: https://www.sciencedirect.com/science/article/pii/S1361920920307501.

Vatcheva, Kristina P et al. (Apr. 2016). "Multicollinearity in Regression Analyses Conducted in Epidemiologic Studies". In: *Epidemiology (Sunnyvale)* 6.2. Epub 2016 Mar 7, p. 227. ISSN: 2161-1165. DOI: 10.4172/2161-1165.1000227. URL: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4888898/.

Vera-Villarroel, Pablo et al. (Aug. 2016). "Perception of Safety and Liking Associated to the Colour Intervention of Bike Lanes: Contribution from the Behavioural Sciences to Urban Design and Wellbeing". In: *PLOS ONE* 11.8, pp. 1–15. DOI: 10.1371/journal.pone.0160399. URL: https://doi.org/10.1371/journal.pone.0160399.

Verhoeven, Hannah et al. (2018). “Differences in physical environmental characteristics between adolescents’ actual and shortest cycling routes: a study using a Google Street View-based audit”. In: *International Journal of Health Geographics* 17. ISSN: 1476-072X. DOI: https://doi.org/10.1186/s12942-018-0136-x. URL: https://ij-healthgeographics.biomedcentral.com/articles/10.1186/s12942-018-0136-x#citeas.

Vidal-Tortosa, Eugeni and Robin Lovelace (2024). “Road lighting and cycling: A review of the academic literature and policy guidelines”. In: *Journal of Cycling and Micromobility Research* 2, p. 100008. ISSN: 2950-1059. DOI: https://doi.org/10.1016/j.jcmr.2023.100008. URL: https://www.sciencedirect.com/science/article/pii/S2950105923000086.

Visual Crossing (2024). *Weather Data*. URL: https://www.visualcrossing.com/.

Walker, Joan L. et al. (Mar. 2018). “D-efficient or deficient? A robustness analysis of stated choice experimental designs”. In: *Theory and Decision* 84.2, pp. 215–238. ISSN: 1573-7187. DOI: 10.1007/s11238-017-9647-3. URL: https://doi.org/10.1007/s11238-017-9647-3.

Wang, Y. et al. (2016). “A review on the effects of physical built environment attributes on enhancing walking and cycling activity levels within residential neighborhoods”. In: *Cities* 50, pp. 1–15. ISSN: 0264-2751. DOI: https://doi.org/10.1016/j.cities.2015.08.004. URL: https://www.sciencedirect.com/science/article/pii/S0264275115001158.

Wardman, Mark (1988). “A Comparison of Revealed Preference and Stated Preference Models of Travel Behaviour”. In: *Journal of Transport Economics and Policy* 22.1, pp. 71–91. ISSN: 00225258. URL: http://www.jstor.org/stable/20052836 (visited on 11/18/2024).

Weller, Bridget E. et al. (2020). “Latent Class Analysis: A Guide to Best Practice”. In: *Journal of Black Psychology* 46.4, pp. 287–311. DOI: 10.1177/0095798420930932. URL: https://doi.org/10.1177/0095798420930932.

West8 (2024). *Revitalization of the Coolsingel*. URL: https://www.west8.com/projects/revitalization-of-the-coolsingel/.

Winters, Meghan et al. (2013). “Mapping Bikeability: A Spatial Tool to Support Sustainable Travel”. In: *Environment and Planning B: Planning and Design* 40.5, pp. 865–883. DOI: 10.1068/b38185. URL: https://doi.org/10.1068/b38185.

Yang, Yiyang et al. (2019). “Towards a cycling-friendly city: An updated review of the associations between built environment and cycling behaviors (2007–2017)”. In: *Journal of Transport Health* 14, p. 100613. ISSN: 2214-1405. DOI: https://doi.org/10.1016/j.jth.2019.100613. URL: https://www.sciencedirect.com/science/article/pii/S2214140519301033.

Zeng, Qisheng et al. (2024). “Measuring cyclists’ subjective perceptions of the street riding environment using K-means SMOTE-RF model and street view imagery”. In: *International Journal of Applied Earth Observation and Geoinformation* 128, p. 103739. ISSN: 1569-8432. DOI: https://doi.org/10.1016/j.jag.2024.103739. URL: https://www.sciencedirect.com/science/article/pii/S1569843224000931.

Zimmermann, Maëlle et al. (2017). “Bike route choice modeling using GPS data without choice sets of paths”. In: *Transportation Research Part C: Emerging Technologies* 75, pp. 183–196. ISSN: 0968-090X. DOI: https://doi.org/10.1016/j.trc.2016.12.009. URL: https://www.sciencedirect.com/science/article/pii/S0968090X16302637.

A

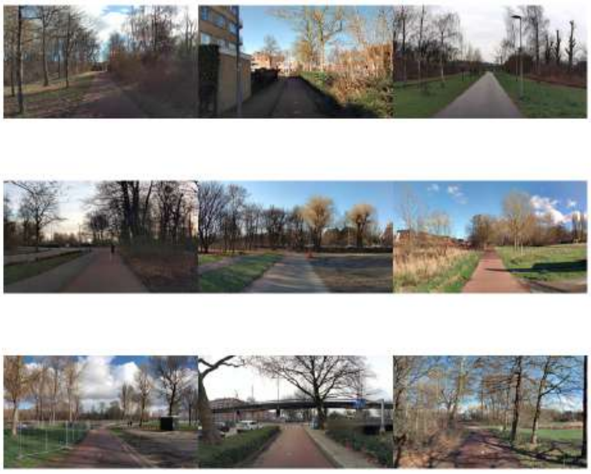
Factors influencing cycling route choice behaviour

Category	Sub category	Factors	Expected influence	Information general sense
Cycling environment	Infrastructure	Cycling facility	Positive	Traffic safety
		Bike lane width	Positive	Traffic safety
		Road surface		Traffic safety
		Tram line	Negative	Traffic safety
		Two lane cycling		Traffic safety
		Roadway type		Traffic safety
		Speed bumps		Traffic safety
		Intersection type		Traffic safety
		Traffic signs		Traffic safety
		Traffic lights		Traffic safety
	Build environment	Buildings		
		Water	Positive	Aesthetics, temperature
		Greenery	Positive	Aesthetics, shade, dryness, temperature
		Lightning	Positive	Social safety
		Security cameras	Positive	Social safety
		Construction work	Negative	Aestethics
		Parking spaces next to lane		
		Obstacles next to or at cycling lane		
		Land use		
	Traffic	Four wheelers	Negative	
		Two wheelers	Negative	
		People		
		Car speed	Negative	Traffic safety
	Other environmental	Nature of terrain	Negative	Extra effort
External factors		Weather		
		Day / night		
		Time of day		
		Air pollution	Negative	Health
		Noise pollution	Negative	Health
Trip characteristics		Travel time		Extra effort
		Travel distance		Extra effort
		Number of intersections		Extra effort / traffic safety
		Number of turns		Extra effort / traffic safety
Personal characteristics	Socio - Demographics	Gender		
		Age		
		Income		
		Education		
		Nationality		
		Urbanity		
		Household structure		
		Current commute travel time		
		Primary mode for commute		
		Commuting days per week		
		Occupation employed		
		Occupation student		
	Attitudes	Importance image / traveltime		
		Always same route		
		Bike incidents		
		Like cycling ?		
		Cycling experience		
		Perception towards traffic safety		
		Perception towards social safety		
		Perception towards aestic routes		
		Cycling alone or together		
		Travel purpose		

Table A.1: Factors influencing cycling route choice behaviour

B

Visualisation of the categories



(a) Solitary cycling lane in a recreational area

(b) Solitary cycling lane in a residential area

(c) Solitary cycling lane on a main road

(d) Separated cycling lane in a residential area

(e) Separated cycling lane on a neighbourhood access road

(f) Separated cycling lane on a main road

(g) Cycling suggestion lane on a neighbourhood access road (30 km/ h)

(h) Cycling suggestion lane on a neighbourhood access road (50 km/ h)

(i) Normal road in a residential area (30 km/ h)

(j) Normal neighbourhood access road (30 km/ h)

(k) Normal main road (30 km/ h)

(l) Normal road in a industrial area (30 km/ h)

(m) Normal road in a residential area (50 km/ h)

(n) Normal neighbourhood access road (50 km/ h)

(o) Normal road in a industrial area (50 km/ h)

Figure B.1: Visualisation of the categories

C

Pilot designs

Based on the attributes identified through literature research and the insights gained from the Lectures Molin, 2024, several survey designs were created. To determine a final optimal survey design, a small case study was conducted. The two routes I typically take from my house to the railway station were analysed and incorporated into a choice experiment. Figure C.1 shows the two routes.

The Bergweg (Route 1) in Rotterdam North is a continuous route that has high levels of traffic, with cars typically driving at 50 km/h. Most of the time there is a cycling suggestion lane and there are three traffic lights. The route is slightly faster than route 2. The second route (Route 2) in Rotterdam North is less frequented and comprises numerous turns. The speed limit is mostly 30 km/h. There are a limited number of traffic lights, but a considerable number of uncontrolled intersections.

The survey designs are shown in Figure C.2 and C.3. Survey 1 resembles real-world decisions most, as it incorporates numerous route characteristics and multiple images of the route. Survey 2 also includes multiple images of the route, but with a reduction in attributes to two. There is chosen for traffic lights and travel time as travel time is the most significant factor and traffic lights can be influenced by policy. To keep simplicity Surveys 3 and 4 have a single image and differ in the number of attributes. The surveys were tested on experts and friends and presented to my supervisors from TU Delft and the municipality. From this, some conclusions were derived as written in the report.

Figure C.1: Route example

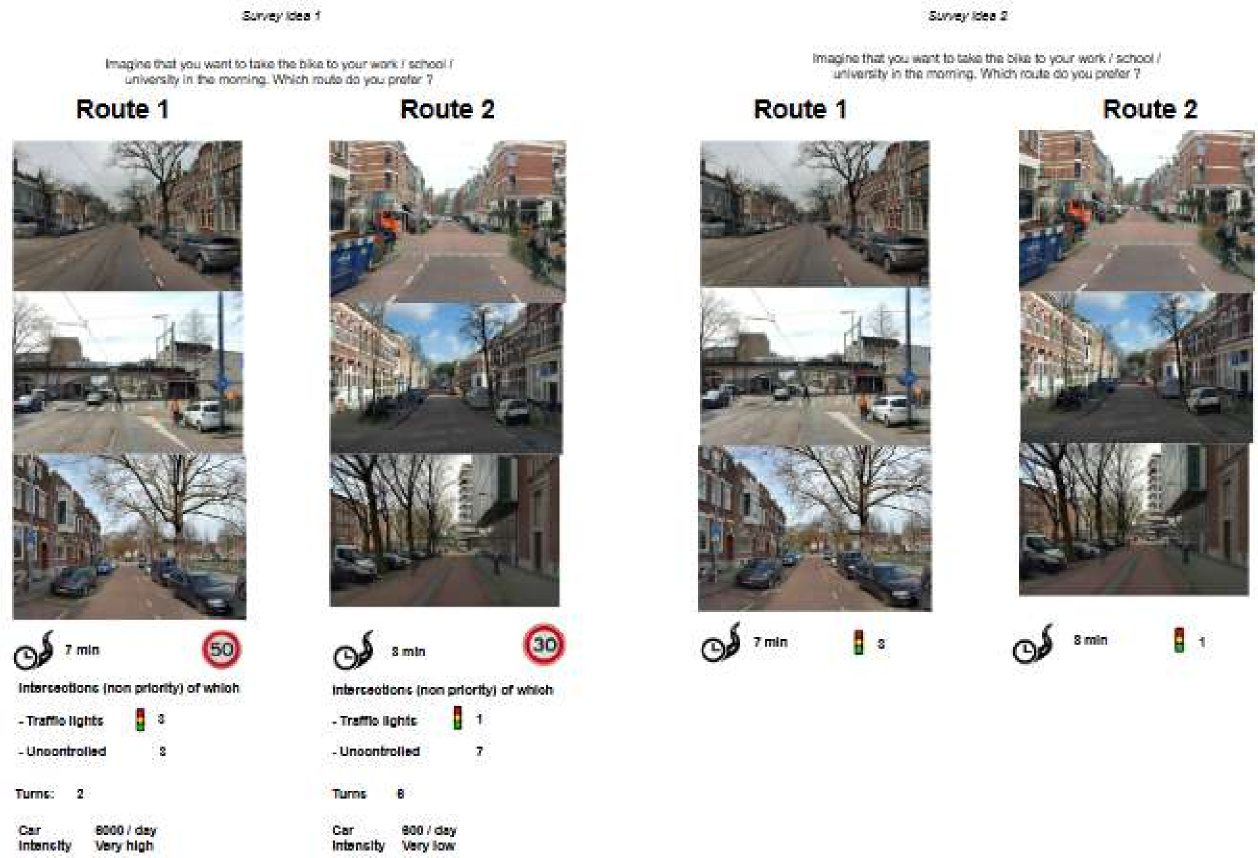


Figure C.2: Survey ideas with multiple images per route

Figure C.3: Survey ideas with one image per route

D

Efficient design code

D.1. Ngene efficient design code pilot survey

```
;alts = alt1, alt2
;rows = 30
;eff = (mnl,d)

;cond:
if(alt1.traveltime = alt2.traveltime, alt1.trafficlights <> alt2.trafficlights)

;model:
U(alt1) = tt[-0.2707]*traveltime[8,11,14] + tl[-0.133]*trafficlights[1,2,3] +
img.dummy[-1.002|-0.921|-0.850|-0.720|-0.663|-0.582|-0.512|-0.471|-0.466|-0.390|-0.319
|-0.273|-0.116|-0.046]*image[0,1,2,3,4,5,6,7,8,9,10,11,12,13,14]/
U(alt2) = tt * traveltime + tl * trafficlights + img * image
$
```

D.2. Efficient design

Choice Situation	alt1.traveltime	alt1.trafficlights	alt1.image	alt2.traveltime	alt2.trafficlights	alt2.image
1	14	1	7	14	3	3
2	11	2	4	11	1	9
3	8	2	1	11	2	4
4	14	3	13	11	3	10
5	11	3	5	11	1	6
6	11	3	10	14	3	9
7	11	1	3	14	3	12
8	8	2	3	8	3	1
9	8	1	4	11	3	11
10	14	2	1	11	2	5
11	8	2	12	8	1	2
12	14	2	6	11	3	4
13	14	2	9	14	3	7
14	11	2	6	8	1	0
15	11	2	11	14	2	13
16	11	3	14	14	1	12
17	14	1	7	11	1	8
18	14	1	8	11	3	6
19	8	3	10	8	1	14
20	11	3	8	8	1	1
21	11	3	2	11	2	5
22	8	2	11	14	2	14
23	14	3	9	14	1	2
24	11	1	13	8	2	3
25	8	1	5	8	2	13
26	14	1	0	14	2	7
27	8	2	2	14	1	11
28	11	2	12	8	2	0
29	8	3	0	11	1	10
30	11	3	14	8	3	8

Table D.1: Efficient design

E

Survey website

Figure E.1 shows the first part of the survey where respondents have to choose between two routes. In addition to the choice situations, respondents were be asked to rate the images on a range of different perceptions. The research conducted by (Zeng et al., 2024) demonstrated that road safety, social safety, and beauty are significant perceptions. These perceptions are valuable for understanding how people experience different cycling environments and for identifying attributes that contribute to perceptions of road safety, social safety, and aesthetics. Due to time constraints, these perception questions were not investigated in this study. However, they could be addressed in further research. Figure E.2 shows the second part of the survey where respondents have to rate an image on traffic safety, social safety and beauty. Figure E.3 and E.4 shows the socio-demographic information and questions asked about cycling.

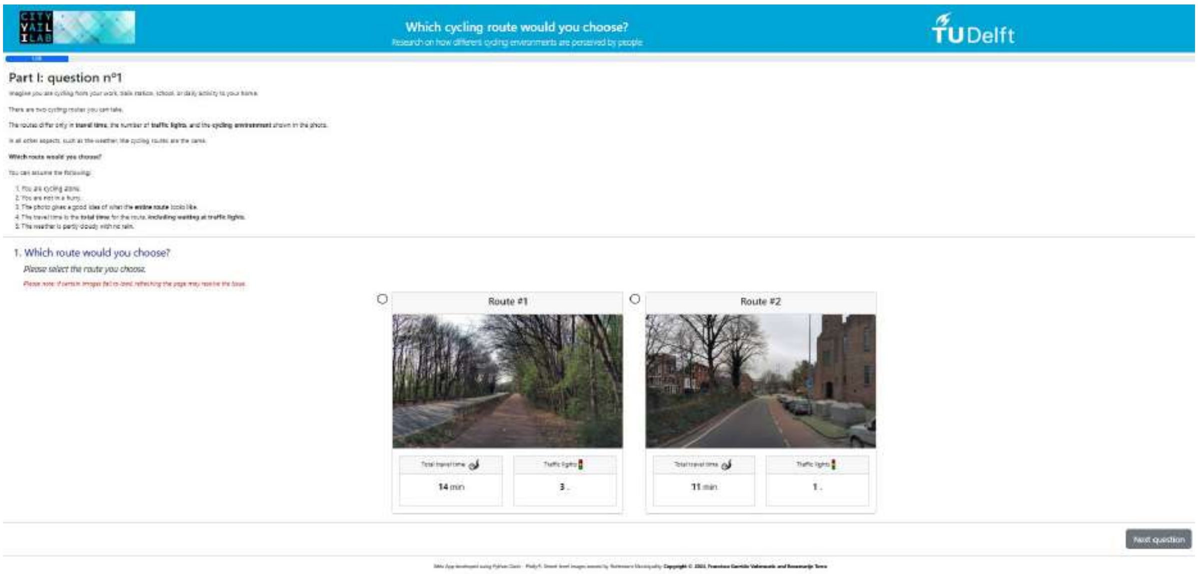


Figure E.1: Survey Part I

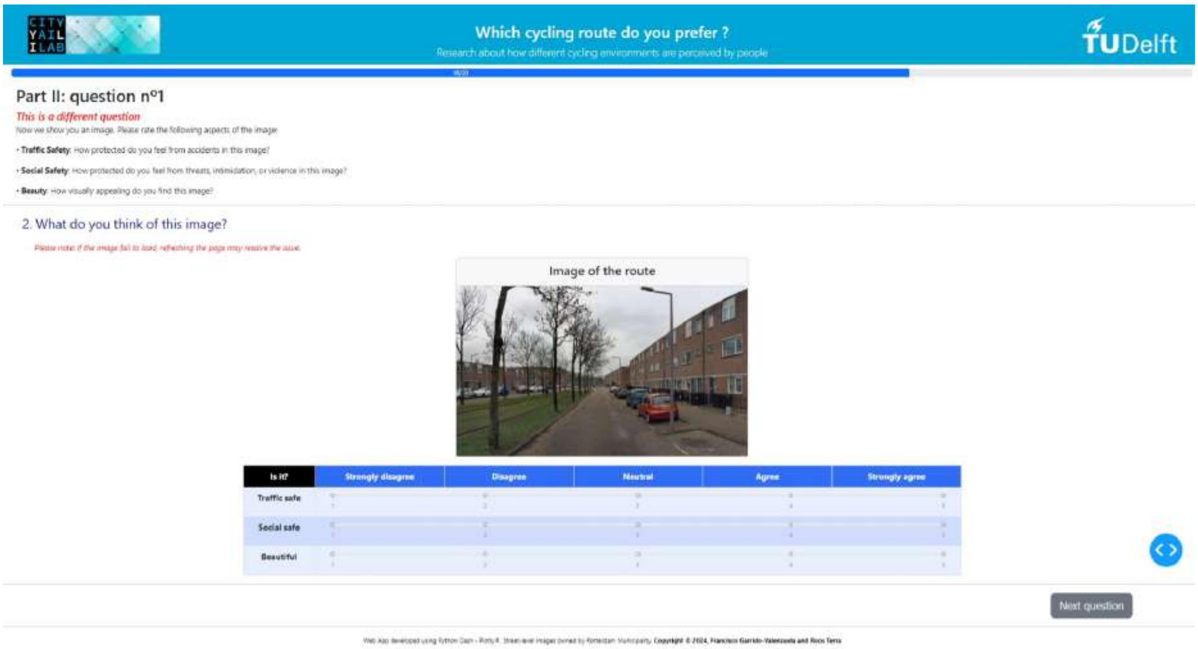


Figure E.2: Survey Part II

How important were the photos, travel time and traffic lights to you in making the cycling route choices (Part 1 of the survey)?

1. On a scale of 1 to 10, how important were the photos to you in making the cycling route choices?

Select an option

2. On a scale of 1 to 10, how important was the travel time to you in making the cycling route choices?

Select an option

3. On a scale of 1 to 10, how important were the traffic lights to you in making the cycling route choices?

Select an option

Tell us a bit more about yourself

1. What is the composition of your household?

A "household" consists of people who usually live together, eat, share costs, etc.

Select an option

2. How many people are currently living in your household, including yourself?

Select an option

3. What is your joint net monthly household income?

Benefits, pensions or alimony are also income. This does not include holiday pay, child benefit and discounts and allowances that you receive from the Tax Authorities (such as healthcare allowance, rental allowance, child allowance and childcare allowance) or refunds from the Tax Authorities.

Select an option

4. How easy or difficult is it for your household to make ends meet with your current income?

Select an option

5. What is your highest level of education that you completed?

Select an option

6. How well is your Dutch?

Select an option

7. What is your most frequent mode of transportation?

Select an option

8. How many cars does your household own?

Select an option

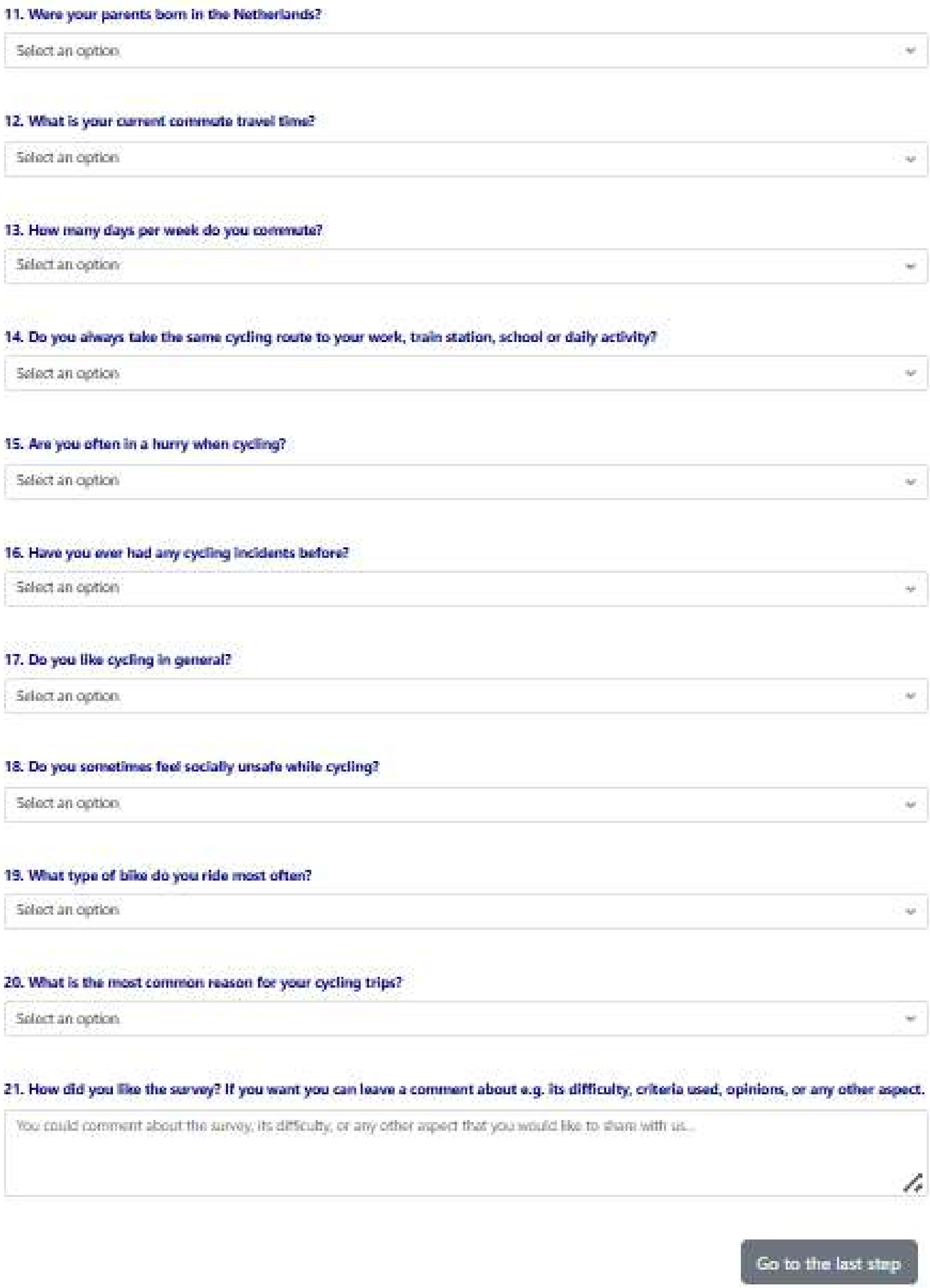
9. How many hours do you work per week in paid employment?

Select an option

10. Were you born in the Netherlands?

Select an option

Figure E.3: Socio-demographics Part I



11. Were your parents born in the Netherlands?

Select an option

12. What is your current commute travel time?

Select an option

13. How many days per week do you commute?

Select an option

14. Do you always take the same cycling route to your work, train station, school or daily activity?

Select an option

15. Are you often in a hurry when cycling?

Select an option

16. Have you ever had any cycling incidents before?

Select an option

17. Do you like cycling in general?

Select an option

18. Do you sometimes feel socially unsafe while cycling?

Select an option

19. What type of bike do you ride most often?

Select an option

20. What is the most common reason for your cycling trips?

Select an option

21. How did you like the survey? If you want you can leave a comment about e.g. its difficulty, criteria used, opinions, or any other aspect.

You could comment about the survey, its difficulty, or any other aspect that you would like to share with us...

Go to the last step

Figure E.4: Socio-demographics Part II

F

Social demographics analysis

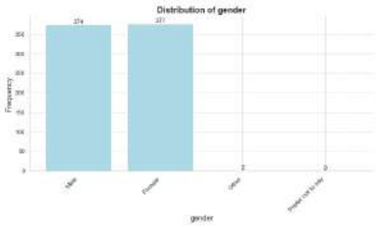


Figure F.1: Gender

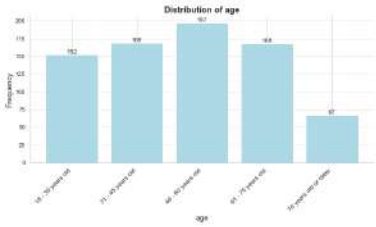


Figure F.2: Age

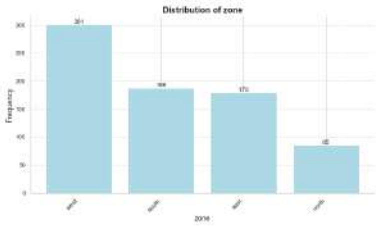


Figure F.3: Zone

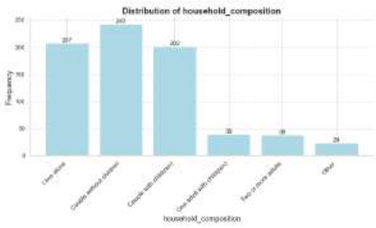


Figure F.4: Household composition

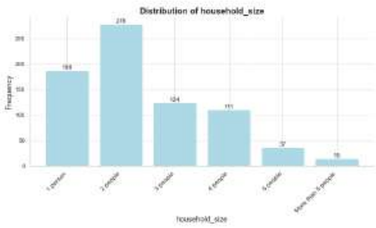


Figure F.5: Household size

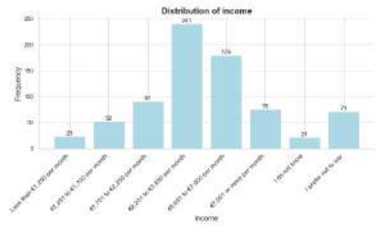


Figure F.6: Income

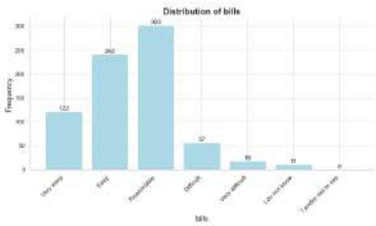


Figure F.7: Bills

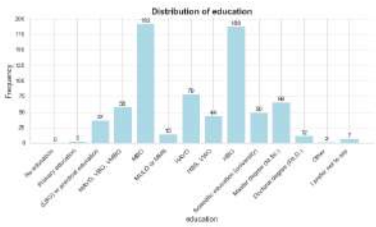


Figure F.8: Education

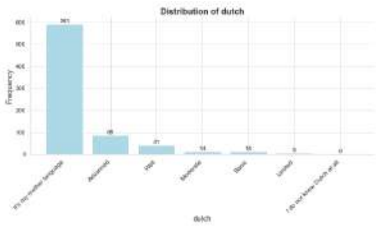


Figure F.9: Dutch language

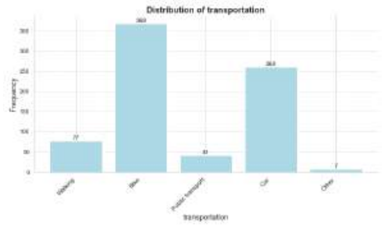


Figure F.10: Transportation mode

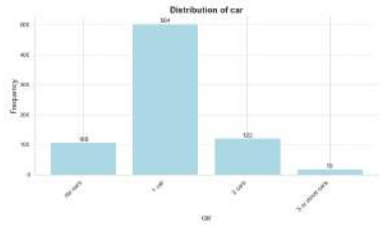


Figure F.11: Amount of cars

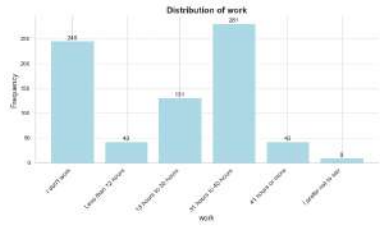


Figure F.12: Work hours

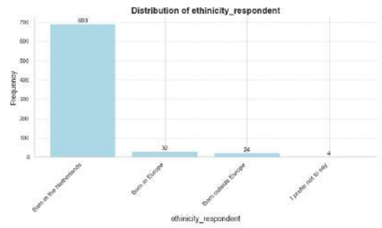


Figure F.13: Ethnicity respondent

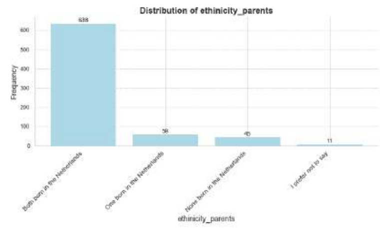


Figure F.14: Ethnicity parents

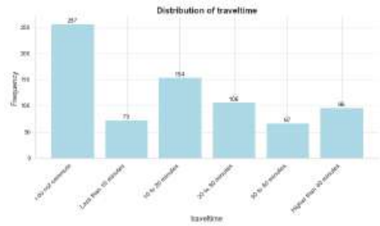


Figure F.15: Commuting time

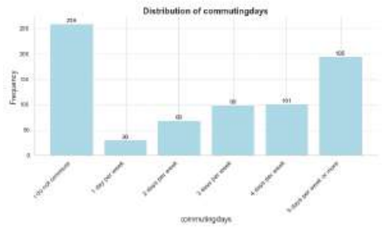


Figure F.16: Commuting days

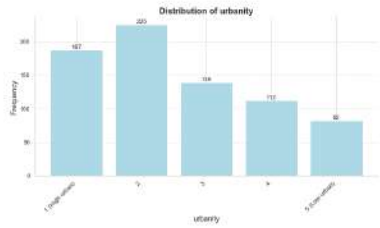


Figure F.17: Urbanity

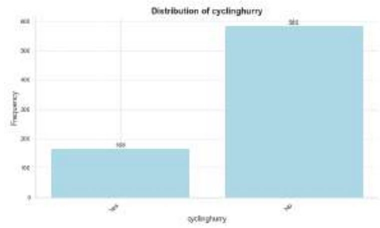


Figure F.18: Cycling hurry

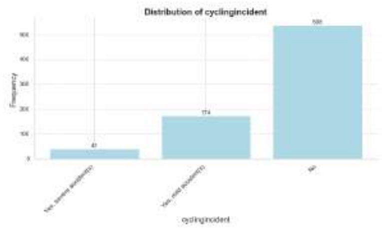


Figure F.19: Cycling incidents

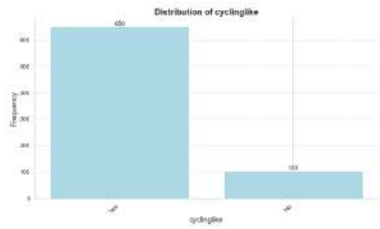


Figure F.20: Cycling like

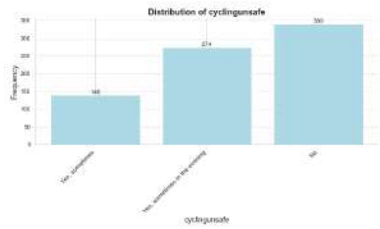


Figure F.21: Cycling perceived safety

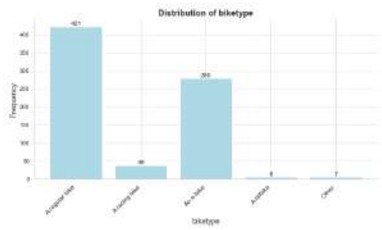


Figure F.22: Cycling incidents

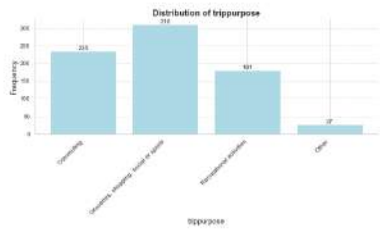


Figure F.23: Cycling like

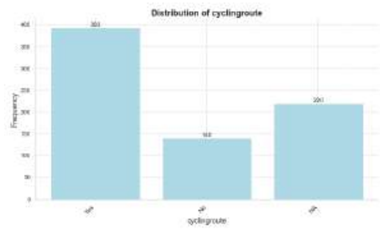


Figure F.24: Cycling route

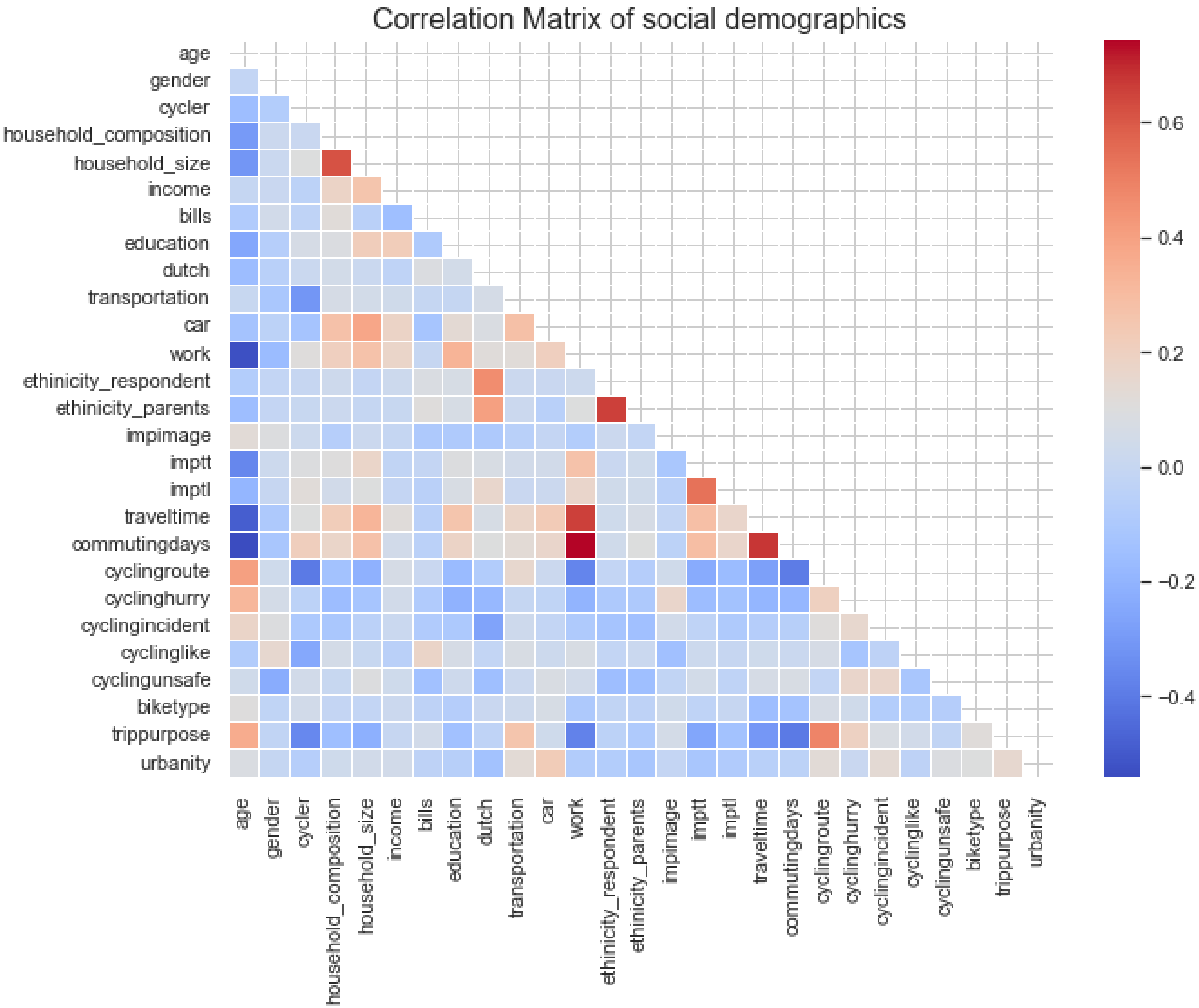


Figure F.25: Correlation between all the social demographics

G
Distribution of answers on the choice situations

Choice Situation	Prior Route 1	Prior Route 2	Survey Route 1	Survey Route 2
1	0.63	0.37	0.70	0.30
2	0.40	0.60	0.11	0.89
3	0.64	0.36	0.72	0.28
4	0.37	0.63	0.32	0.68
5	0.42	0.58	0.40	0.60
6	0.71	0.29	0.66	0.34
7	0.62	0.38	0.54	0.46
8	0.58	0.42	0.73	0.27
9	0.67	0.33	0.46	0.54
10	0.24	0.76	0.21	0.79
11	0.65	0.35	0.59	0.41
12	0.37	0.63	0.52	0.48
13	0.55	0.45	0.77	0.23
14	0.39	0.61	0.34	0.66
15	0.64	0.36	0.65	0.35
16	0.66	0.34	0.62	0.38
17	0.31	0.69	0.39	0.61
18	0.38	0.62	0.46	0.54
19	0.36	0.64	0.25	0.75
20	0.35	0.65	0.30	0.70
21	0.40	0.60	0.25	0.75
22	0.79	0.21	0.65	0.35
23	0.55	0.45	0.54	0.46
24	0.50	0.50	0.51	0.49
25	0.40	0.60	0.56	0.44
26	0.40	0.60	0.57	0.43
27	0.71	0.29	0.55	0.45
28	0.52	0.48	0.49	0.51
29	0.47	0.53	0.39	0.61
30	0.41	0.59	0.55	0.45

Table G.1: Comparison of Prior and Survey Probabilities

H

Predicted utility score cluster analysis

Figure H.1: Images of cluster 1

Figure H.2: Images of cluster 2

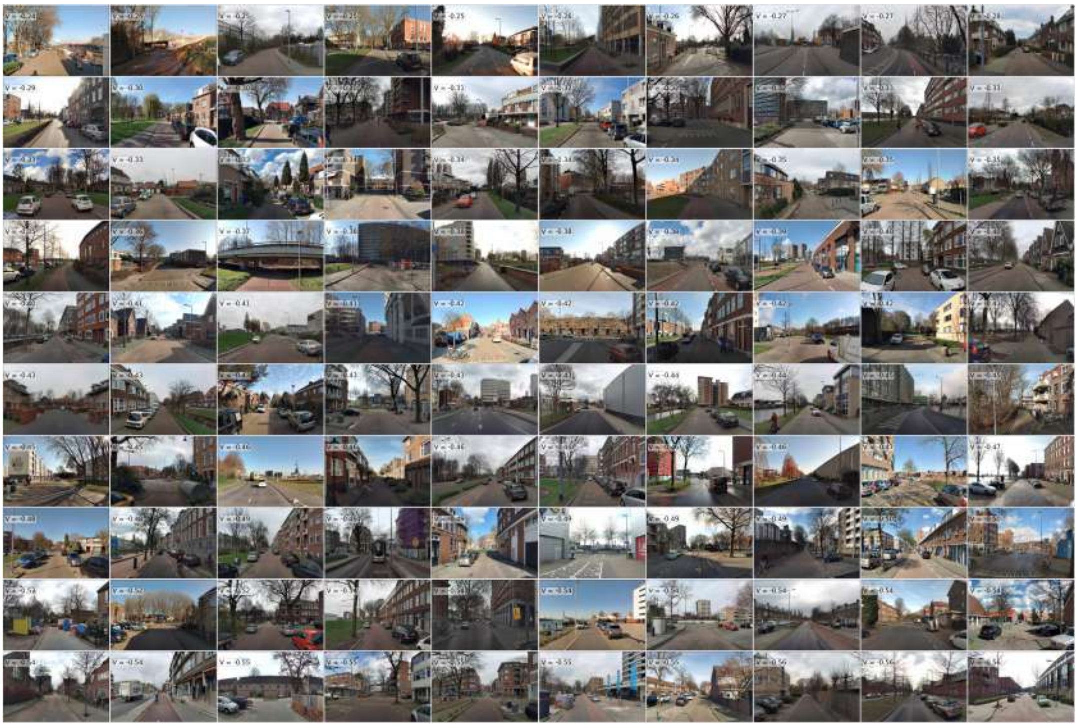


Figure H.3: Images of cluster 3

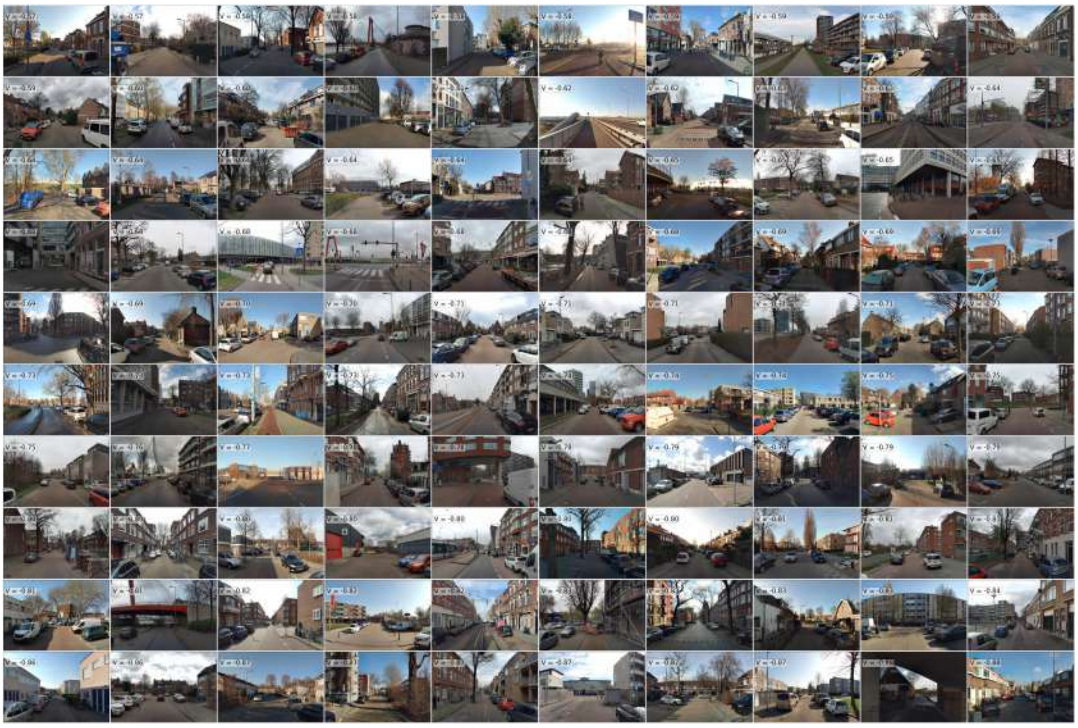


Figure H.4: Images of cluster 4

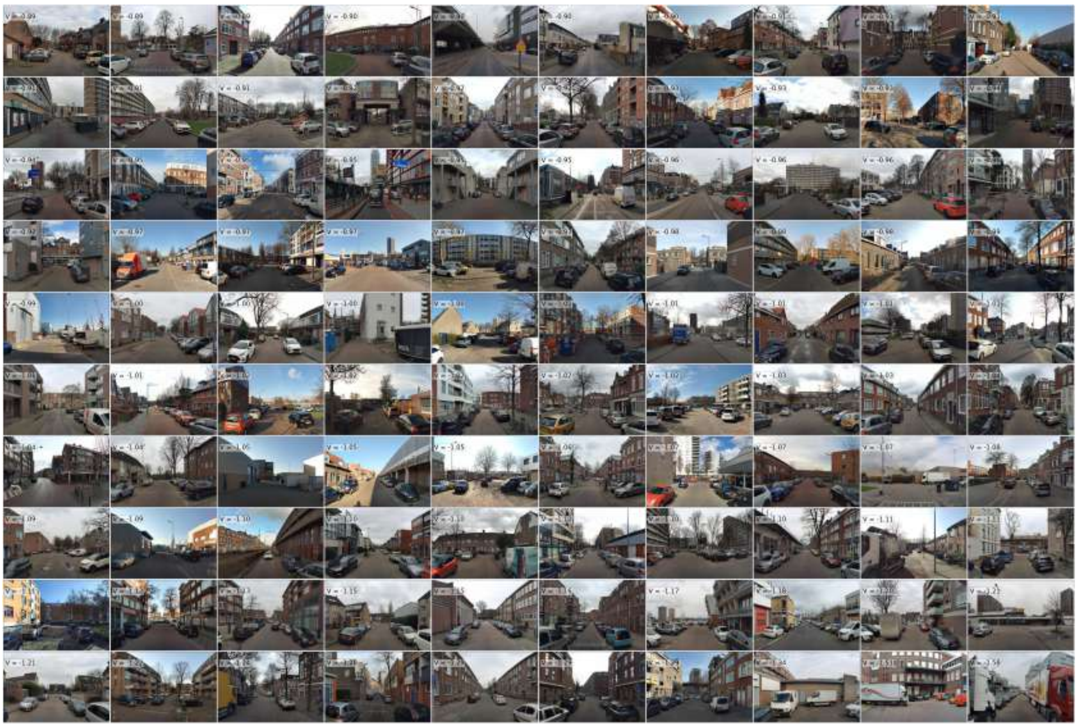


Figure H.5: Images of cluster 5

Understanding cycling route choice behaviour through street-level images and computer vision-enriched discrete choice models

A case study in Rotterdam

R.W. Terra [a], Dr. S. van Cranenburgh [b], Prof. Dr. O. Cats[c], F. Garrido-Valenzuela [d]

[a] *Transport, Infrastructure and Logistics, Delft University of Technology, The Netherlands*
[b] *CityAi Lab, Delft University of Technology, The Netherlands*
[c] *Municipality of Rotterdam, The Netherlands*

Date issued: 12/12/2024

Abstract

This paper investigates cycling route preferences, with a focus on the cycling environment. To represent the cycling environment street-level images were used. A recently proposed model incorporates computer vision into a traditional discrete choice model to accommodate choice tasks involving numerical attributes and images. This computer vision-enriched discrete choice model (cv-dcm) was applied using a stated choice experiment, where respondents had to choose between two cycling routes. Each route was defined by three attributes, including commute time, number of traffic lights, and the cycling environment, the latter visualised using street-level images. While the cv-dcm relies on a neural network, making interpretability challenging, this study addressed this by collecting detailed cycling environment attributes. Results showed that the cycling environment was the most influential factor, with cyclists preferring green areas and separated cycling lanes. On average, cyclists were willing to take a 1.5-minute detour for a cycle trip of 11 minutes to use a separated cycling lane instead of a mixed-traffic road. These insights offer valuable insights for policymakers aiming to design cycling environments that align with cyclists' preferences.

Keywords: discrete choice models, computer vision, street level imagery, stated choice experiment, cycling routes, cycling environment

1 Introduction

The Netherlands is a country with a high level of cycling activity. The number of kilometres cycled has increased by 23% over the period 2000 - 2022, and this trend is expected to continue (KiM, 2023). There are numerous advantages to this high level of cycling activity; it is beneficial for health and contributes to many other goals, including accessibility, sustainability and liveability (Dutch Cycling Embassy, 2018). The 2015 Paris Climate Agreement set a target to reduce CO2 emissions by at least 40% by 2030 (I&W, 2020). Achieving these climate goals underscores the importance of sustainable mobility solutions, such as cycling (European Union, 2023).

The growing number of cyclists in Rotterdam places substantial pressure on the Rotterdam's cycling infrastructure, which is caused by significant population growth and the rising demand for sustainable transport (CBS, 2024b). Over the past decade, the number of cyclists has increased with a 60% in Rotterdam (Gemeente Rotterdam, 2019b). Currently, 62% of all movements in Rotterdam are made by bicycle, on foot, or via public transport, reflecting the city's shift toward sustainable mobility (Gemeente Rotterdam, 2019a). Furthermore residents of Rotterdam frequently perceive a lack of safety in the city's traffic. A survey resulted in the identification of over 7000 unsafe locations within a three-week period (Gemeente Rotterdam, 2023). A significant number of these locations were associated with the cycling environment.

While perceived safety is an essential component, it represents only one aspect of the overall cycling experience. Cyclists' experiences are also influenced by for example comfort and aesthetics. Therefore, the focus shifts from perceived safety to the overall perceived cycling experience. Currently, the assessment of cycling experience is primarily conducted through surveys and interviews (Gemeente Rotterdam, 2023). The perceived cycling experience is dependent on the route cyclists select for their trip. Some people may be motivated to minimise travel time, while others may prioritise cycling through safe and aesthetic environments or avoiding traffic lights (Prato, 2009). Understanding these preferences is important for designing a cycling environment that aligns closely with the preferences of its cyclists, making cycling a safe and appealing mode of transport. This requires an analysis of route choice behaviour.

2 Literature review

The literature review discusses the current state concerning influencing factors on cycling route choices, and also elaborates on computer vision methods and the use of street-level images. The final section presents a concise summary of the current state of knowledge, highlighting areas where further research is needed and suggesting potential directions for further investigation.

2.1 Cycling route choice behaviour

Extensive research has been conducted on factors that influence cycling route choice behaviour. This includes travel time, the built environment, cycling infrastructure, the natural environment, the number of intersections and turns, but also social demographics and the purpose of the trip (Heinen et al., 2010; Kaplan and Prato, 2015; Ton et al., 2017; Zimmermann et al., 2017). The majority of these studies have employed GPS data, interviews and stated preference surveys.

For many individuals, the most crucial factor in cycling route choice is travel time or distance. A study by Verhoeven et al. (2018) based on GPS data in Belgium revealed that 71% percent of respondents did not diverge from the shortest possible cycling route. Another important factor to consider is the number of intersections along the route. Cyclists tend to avoid traffic lights due to the potential for long waiting time (Ton et al., 2017). The number of turns also contributes to a sense of disutility. It is often the case that cyclists will choose for the most straightforward route, which is the route with a minimal number of turns (Verhoeven et al., 2018).

The cycling environment is important in determining cycling route choice behaviour. This includes not only the physical infrastructure, but also the surrounding built environment, traffic and other environmental influences. Infrastructure characteristics that are likely to influence cycling route choice behaviour include for example the presence of a cycling lane, the width of the cycling lane (Gössling and McRae, 2022), the type of cycling lane (segregated or shared) (Kaplan and Prato, 2015), whether it is shared with a tram line (Kaplan and Prato, 2015), the road surface (Zimmermann et al., 2017) and if there are parking spaces next to the cycling lane (Gössling and McRae, 2022). Additionally, previous studies of the relationship between the built environment and cycling have demonstrated that several built environment factors are associated with cycling behaviour (Heinen et al., 2010; Wang et al., 2016). According to the review paper of Yang et al. (2019) there are relations with the amount and type of buildings, greenery, water, public facilities and population density. Furthermore, the presence and speed of other traffic, such as cars, trams, cyclists, e-bikes, cargo bikes, and pedestrians, influence cycling route choice (Misra and Watkins, 2018). Additionally, it is important to consider the influence of natural environment factors. The weather can have an impact, as can the lighting on the image (Vidal-Tortosa and Lovelace, 2024).

Some studies used a stated choice experiment with generated images (Rossetti et al., 2018), but most studies have presented cycling environment attributes as text descriptions. Text-based representations of the cycling environment are challenging for individuals to interpret, potentially leading to invalid results (Elu et al., 2021). In contrast, using images offer a richer and more realistic way of evaluating respondent's preferences, making them an optimal choice for stated choice experiments.

2.2 Perception and computer vision

In the last decade developments in computer vision and street view images have provided methodologies for understanding the effects of visual features of the environment on the way they are perceived (Dubey et al., 2016; Ma et al., 2021; Rossetti et al., 2019). It has been demonstrated, using real-world images, that the cycling environment significantly influences various perceptions, such as traffic safety, social safety, and beauty (Ito and Biljecki, 2021; Juarez et al., 2023; Zeng et al., 2024).

However, there is limited research on how the cycling environment influences preferences for cycling routes. Preferences are crucial as they directly inform choice behaviour, whereas perceptions alone shape impressions but do not necessarily result in choosing a specific cycling route. While a route may be perceived as beautiful and safe, if the travel time is unacceptably long, it will not be chosen. Perceptions lack these kind of trade-offs, which is necessary to analyse potential cycling environment improvements effectively. It is therefore essential to consider the preferences of individuals instead of the perceptions.

2.3 Knowledge gap

It has been determined that it is challenging to make an informed choice regarding cycling routes based solely on textual information. Additionally, studies, utilising real-world images, have identified that the cycling environment influences people's perceptions. However, there is limited research on how the cycling environment influences preferences for cycling routes. Displaying cycling environments visually can facilitate a deeper understanding of individuals' preferences regarding cycling environments in the context of cycling route choices. To the authors knowledge no studies have investigated this. By identifying these preferences, the study aims to inform the municipality of Rotterdam on effective strategies on designing cycling environments.

The recently proposed model of Cranenburgh and Garrido-Valenzuela (2023) can accommodate choice tasks involving numerical attributes and images by integrating computer vision into a traditional discrete choice model. This model is referred to as the computer vision-enriched discrete choice model (cv-dcm). The cv-dcm is able to assign a predicted cycling environment utility score to each image providing a valuable measure of the perceived cycling environment. The model is not straightforward for humans to interpret, given that it is based on neural networks. So the reason behind the assignment of a specific score to a given image remains complex. It is therefore important to analyse the model using a combination of qualitative, spatial and quantitative analyses. A validity check has to be conducted to analyse whether the cv-dcm aligns with expected human decision-making in cycling route choice. Furthermore, it is valuable to analyse how different cycling environments and infrastructure characteristics affect the utility score. From a policy perspective, an interpretable model is particularly valuable. Explaining the factors that contribute to the utility score allows to design cycling environments that meets the preferences of cyclists.

3 Methodology

3.1 Discrete choice models (DCM)

A computer vision-enriched discrete choice modelling (cv-dcm) method will be employed to predict cycling route choice. Initially, the conventional random utility maximisation-multinomial logit discrete choice model (RUM-MNL) will be explained. Section 5.2 describes the computer vision component.

Discrete choice models are used to explain and predict a choice from a set of two or more discrete alternatives (Sifringer et al., 2020). It has been applied as a mathematical tool to model route choices for more than forty years. It considers an economic and quantitative approach with the assumption that each choice made is the outcome of a rational choice process (Columbiauniversity, 2020).

Daniel McFadden developed the well-known Random Utility Maximisation (RUM) Model. This model assumes that the decision-maker will choose the alternative that maximises their utility (McFadden, 1974). The utility of an alternative is comprised of the observed- and the unobserved utility. The observed utility is based on observed attributes that are expected to impact the decision. The unobserved utility is based on everything else that governs the individual's choice. This utility is randomly distributed across all individual choices, contributing to the stochastic nature of discrete choice models. Equation 1 shows the equation for utility U for alternative i.

The objective of the maximum likelihood estimation is to identify the beta parameters that make the data most likely, thereby determining the beta parameters that maximise the log likelihood (LL) function. The model will estimate the weight of all these observed attributes. The standard equation of the linear-additive RUM model is shown in equation 2. Based on these weights, it is possible to calculate the probability that a respondent will choose a certain alternative. This can be done with the multinomial logit model (MNL). In MNL models, the error terms are independently and identically Extreme Value Type I distributed (i.i.d.) with variance $\frac{\pi^2}{6}$. Equation 3 shows the form of the linear-additive MNL model.

$$U_i = V_i + \varepsilon_i \tag{1}$$

$$U_i = \sum_m \beta_m \cdot x_{im} + \varepsilon_{in} \tag{2}$$

$$P_{in} = \frac{e^{V_{in}}}{\sum_j e^{V_{jn}}} \tag{3}$$

3.2 Computer Vision enriched Discrete Choice Modelling (cv-dcm)

Images offer an additional source of data for explaining choice behaviour. In many choice situations it is hard to make a choice without visual information. For example in residential location choice (Cranenburgh and Garrido-Valenzuela, 2023), cycling route choice and tourist destination choice (Pan et al., 2021). Recently, Cranenburgh and Garrido-Valenzuela (2023) have proposed a new class of discrete choice models –called Computer Vision-enriched Discrete Choice Models (cv-dcms). This new method regarding residential location choice will be applied in this research. An extensive explanation of the computer vision part of this method can be found in their research. A summary of the methodology will be provided in this section.

CV is a crucial technology for extracting information from visual data. In this research CV will be used to convert images into meaningful data that can be applied to contribute in the DCM. CV models are designed to detect scenes and objects incorporating over one billion weights in the largest models. Images are composed of pixels, whereby each pixel contains three colour channels, namely red, green and blue (RGB) and a location, namely height and width (h x w). The images are represented as three dimension tensors, which are multi-dimensional arrays of numerical values. These tensors facilitate efficient image processing, with the three dimensions corresponding to width, height, and colour channels. A typical image contains millions of pixels. However, directly using pixel in a CV model is not efficient due to the amount of data and the limited information that individual pixels have. Therefore the CV model to be applied consists of a feature extractor and a classifier. The feature extractor generally is a deep neural network and is responsible for extracting relevant features of the images. It comprises a relatively modest 86 million weights. The output of the feature extractor is the feature map which is a flat array of floating points with a size of 1 x 1000. So the feature map is comprised of most of the information that can be seen in the image and is readable for the computer, while also being of an appropriate scale. The working of the CV model is displayed in Figure 1. The pre-trained feature extractor from the DeiT base model will be applied (Data-efficient image Transformer). DeiT models are vision transformer-based architectures known for their data efficiency, achieving competitive performance on benchmark datasets like ImageNet (ImageNet, 2024) while requiring less computational power and data than many other models (Touvron et al., 2021).

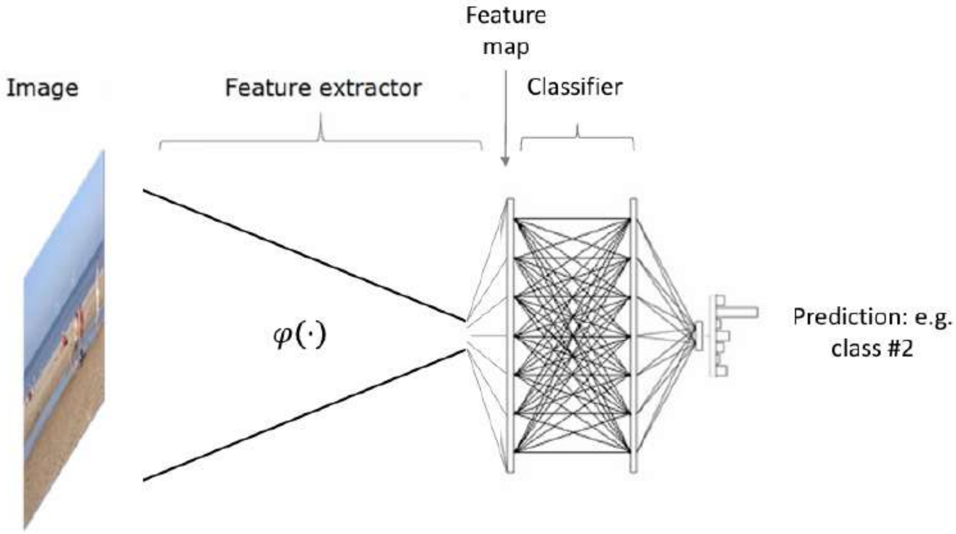


Figure 1: Feature extraction and classification.
Adopted from Cranenburgh and Garrido-Valenzuela (2023)

The image represented by the feature map is applied in conjunction with the numerical attributes in the utility function. Subsequently, the probability that a respondent will choose a certain alternative can be estimated. This is achieved through the use of a Multilayer Perceptron (MLP), a type of a deep neural network, which functions in a manner identical to that of a standard DCM. Equation 4 illustrates the derivation of utility, whereby the first part denotes the utility associated with the numerical attributes, the second part denotes the utility associated with the image, and the third part denotes the error term. Figure 2 shows the model structure of the cv-dcm.

$$U_i = \underbrace{\sum_m \beta_m \cdot x_{im}}_{\text{Utility derived from numerical attributes}} + \underbrace{\sum_k \beta_k \cdot z_{ik}}_{\text{Utility derived from image feature map}} + \varepsilon_{in} \tag{4}$$

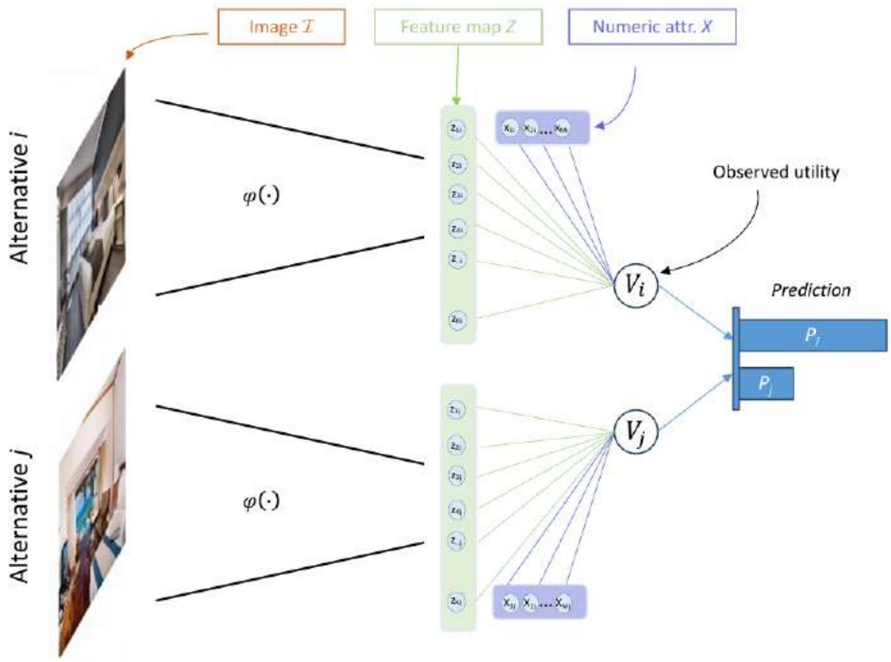


Figure 2: Model structure of the cv-dcm.
Adopted from Cranenburgh and Garrido-Valenzuela (2023)

4 Data collection

4.1 Street-level image collection

Street-level images are applied to determine the visual cycling environment of cycling paths for the stated choice model. Each cycling path requires a street-level image of the surrounding area. The city of Rotterdam is selected for this study. The study considers most of the residential and commercial areas of Rotterdam excluding its port and surrounding areas. All cycling lanes within the study area are included. The municipality of Rotterdam has a database of street level images with a total of more than 600,000 images. Images are captured on nearly every road, and they are also taken on the cycling lanes (Cyclomedia, 2023). Also, the location and direction of each image is recorded.

The cycling network, adopted from Fietsersbond (2020), is generated within the geographic information system (QGIS, 2023). The cycling network is constructed of segments, which are defined as stretches of cycling path that begin at an intersection and end at another intersection. Subsequently for each segment, a point is created in the middle of the segment, resulting in a grid of points. The nearest street-level image for each point on the grid is retrieved. In the absence of an image within a four-metre radius of a given point, no image is included. This approach is applied to avoid the retrieval of images from locations unsuitable for cycling. In total, approximately 13,000 images were captured.

The images are 360-degree panorama photos, which has to be converted into 90-degree images of the cycling path direction. Only this direction is of interest, as it is aimed to view the front view of the cycling path and not the side view or the back view. This is done based on the direction of the cycling lane and given that the centre of the panorama image is always oriented towards the north.

4.2 Street-level image analysis

All characteristics that influence cycling environment scores has to be visible in the images for the survey, otherwise the model will be unable to assess these images effectively. To ensure that all characteristics are included it is important to examine all different types of cycling paths and environments.

Furthermore knowledge about attribute levels is crucial for the construction of the survey. However images lack attribute levels. This issue is addressed by analysing images based on the cycling path and their environment through GIS analyses. On this way, a ranking of the images is established. This information will then be utilised to determine which images will be selected for comparison in the stated choice experiment.

A review of the literature reveals that the choice of cycling route is frequently influenced by the type of cycling lane (Gössling and McRae, 2022; Kaplan and Prato, 2015; Zimmermann et al., 2017). Additionally studies have demonstrated that there is a relationship between several built environment features and cycling behaviour (Heinen et al., 2010; Wang et al., 2016). Findings of Misra and Watkins (2018) revealed that traffic characteristics such as speed and the amount of traffic influence the decision to choose a cycling route. Based on the literature and data available the decision was taken to classify the images based on the cycling infrastructure, built environment and speed of the car. Table 1 shows the attributes and their corresponding attribute level.

Cycling Infrastructure	Built Environment	Maximum Speed Car
Solitary cycling lane	Recreational area	Not applicable
Separated cycling lane	Residential area	30 km/h
Normal road	Neighbourhood access	50 km/h
Cycling suggestion lane	Main road	
	Industrial area	

Table 1: Attributes and their corresponding attribute levels

All images are sorted according to cycling infrastructure, built environment and maximum speed of the car. The decision was taken to categorise the images according to the 15 most common categories. Categories with few images have been merged with a category that is very similar. Each category contained more than 150 images. This was deemed necessary to prevent the same images from a less common category from appearing multiple times in the survey. This applied methodology guarantees the inclusion of all essential features and enables the establishment of a ranking of the images.

4.3 Cycling environment data collection

Information about the cycling environment is collected. This is used to interpret the cv-dcm and to develop a model that will examine the impact of different infrastructure elements and built environment characteristics on cycling route choice.

4.3.1 Data collection

Built environment: The built environment was obtained mainly through the use of the 'Basisregistratie Grootschalige Topografie' (BGT, 2024). This is a public dataset of the Netherlands, which is used to manage the design and configuration of the built environment. The dataset includes a range of objects, including buildings (e.g., residential houses, offices, schools), roads (e.g., motorways, parking spaces, cycling and walking lanes), water (e.g., rivers, lakes, canals, ponds), and greenery (e.g., trees, grass, plants). The BGT is accurate within a margin of 20 centimetres, providing an optimal approach for obtaining the environment behind the image.

Cycling infrastructure data: The BGT also records information about road characteristics, such as pedestrian lanes, speed bumps, tram infrastructure and cycling lane characteristics (width, colour and pavement type).

Weather and Light: The date and time of the capture of the street-level images are known. This allows the retrieval of the weather conditions by matching them with the date and time. The weather data is accessed via (Visual Crossing (2024)), a public dataset where hourly weather data for years back can be downloaded for free. A variable representing either sunny or cloudy weather was created. In addition, the brightness value of each image was calculated using a python script.

Population density: Centraal Bureau of Statistiek (CBS) has data about macro-level built environment variables, including population density (CBS, 2024a). Population density data is available for each district, neighbourhood, and municipality in the Netherlands.

4.3.2 Match attributes with the image

Once all the data has been collected, it needs to be matched with the images. For instance, if the image displays water, the corresponding numerical value for water should be assigned the value of "1". This process was also applied to all other attributes. For plants, grass, car parking and trams, a distance of 10 metres proved to be a good threshold. For attributes that are higher and larger, such as trees and buildings, a larger distance was employed, as these attributes remain visible even at greater distances. For trees, instead of a binary level with either no trees or trees, it is counted how many trees there are on a segment. Since there are trees almost everywhere and trees are easy to count, this method was applied. However the difference in segment length introduces a degree of inaccuracy into this method. Table 2 presents a comprehensive list of all the collected attributes, along with the data sources and the manner in which they are linked with the image.

Attribute	Attribute levels	Source	Link
Micro Built Environment			
Trees	Amount of trees	BGT	Segment buffer within 20 meters
Grass	Yes / no	BGT	Within 10 meters
Plants	Yes / no	BGT	Within 10 meters
Water	Yes / no	BGT	Within 20 meters
Buildings	Yes / no	BGT	Within 20 meters
Industrial buildings	Yes / no	BGT	Within 20 meters
Macro built Environment			
Built Environment type	Recreational Main road Access road Residential area Industrial area	BGT	No distance applied
Population Density	Inhabitants / km	CBS	Within the neighbourhood
Cycling Infrastructure			
Infrastructure type	Normal road Cycling suggestion lane Separated cycling lane Solitary cycling lane	Fietsersbond	Initial network
Pavement type	Asphalt Clinkers	Fietsersbond	Initial network
Parking	Yes / no	BGT	Within 10 meters
Width	Meters	BGT	Within 10 meters
Colour	Red / Not red	BGT	Within 10 meters
Tram on cycling lane	Yes / no	BGT	Within 10 meters
Traffic			
Car intensities	Numeric	Omnitrans	
Cycle intensities	Numeric	Omnitrans	
Car speed	NA 30 50	Rijkswaterstaat	
Other			
Weather	Sunny Cloudy	Visual Crossing	
Lighting	Numeric		

Table 2: Collected attributes

4.3.3 Checking multicollinearity

Correlations between the attributes trees, grass, plants, water, buildings, industrial buildings, parking, tram, pavement, cycling type, weather and brightness were calculated for validation of the data collection as well as to check for multicollinearity. Multicollinearity refers to the situation in which the independent variables are highly correlated with one another. When multicollinearity is present, it can have a number of effects and implications for further analysis. The presence of multicollinearity makes it challenging for the model to determine the unique contribution of each independent variable. Consequently, the coefficient estimates may become unstable and unreliable (Donath et al., 2012). The highest correlation of -0.39, between cycling type and pavement type, is below the threshold of 0.8 (Berry, 1985), indicating that there is no multicollinearity.

4.4 Stated choice experiment (SC)

To design a cycling environment that aligns closely with the preferences of cyclists it is essential to understand their choices when selecting routes. A stated choice experiment determines the independent influence of different attributes on observed outcomes (Rose and Bliemer, 2009). The manner in which the attributes, ranges and underlying design is created is described in this chapter.

4.4.1 Selected attributes and ranges

The selection of attributes for the study is guided by their relevance to individuals' cycling route decision-making and their potential to be influenced by policy and design interventions (Molin, 2024). Previous studies, such as Verhoeven et al. and Bernarde et al. have indicated that most individuals prioritise the shortest route (Bernardi et al., 2018; Verhoeven et al., 2018). Additionally, the number of intersections along a route plays a significant role, as cyclists tend to avoid traffic lights (Ton et al., 2017). Similarly, the number of turns contributes to a sense of disutility, with cyclists often opting for the most straightforward route (Verhoeven et al., 2018). Based on expert input and literature review, the final attributes selected for the survey include the image of the route, travel time, and the number of traffic lights. These attributes capture key factors influencing route choice while allowing for the analysis of policy-relevant variables.

In designing the experiment, three levels were selected for the attributes of travel time and traffic lights to ensure attribute balance, as recommended (Walker et al., 2018). A travel time of approximately 10 minutes was chosen as a realistic duration for typical cycling trips in urban settings such as Rotterdam. To allow comparisons across all levels without creating dominant alternatives, a range of three minutes was defined, resulting in travel time levels of 8, 11, and 14 minutes. The number of levels for traffic lights has been selected to align with that of travel time, namely three. Sometimes in images traffic lights can be seen. Consequently, if zero is designated as the range for traffic lights, the choice task may appear contradictory. Therefore, range for traffic lights are defined as 1, 2, 3.

4.4.2 Efficient design

For this study an efficient design has been selected. This is a type of design where dominant alternatives are excluded. The objective of this design is to achieve a balance between the utilities of the alternatives in the choice situations. This design allows for the maximisation of information about trade-offs and the minimisation of the standard error of the parameters (Rose and Bliemer, 2009). In order to construct an efficient design, it is necessary to obtain priors that balance the utilities of the choice alternatives. The use of inaccurate priors will result in less efficient and biased parameters. Furthermore, when dominance is a significant issue, an efficient design is proved to be more efficient.

There is existing literature on cycling route choice behaviour in the Netherlands, which provides valuable insights and prior knowledge. The priors are obtained from the study of Significance (Significance, 2022). The prior parameters are displayed in Table 3. With these priors an efficient design is created in Ngene. The number of choice situations required is thirty, as this allows for the maintaining of attribute balance. Ngene is a software that allows to create and analyse stated choice experimental designs (ChoiceMetrics, 2024).

Parameter	Beta Value	Cycling infrastructure	Speed Limit	Built Environment
b_time	-0.2707			
b_trafficlights	-0.1330			
b_img.dummy[0]	-1.002	Normal road	50	Access road
b_img.dummy[1]	-0.921	Normal road	50	Industrial
b_img.dummy[2]	-0.850	Normal road	50	Residential
b_img.dummy[3]	-0.720	Cycling suggestion lane	50	Access road
b_img.dummy[4]	-0.663	Normal road	30	Industrial
b_img.dummy[5]	-0.582	Normal road	30	Main road
b_img.dummy[6]	-0.512	Normal road	30	Access road
b_img.dummy[7]	-0.471	Cycling suggestion lane	30	Access road
b_img.dummy[8]	-0.466	Normal road	30	Residential
b_img.dummy[9]	-0.390	Separated cycling lane	N/A	Main road
b_img.dummy[10]	-0.319	Separated cycling lane	N/A	Access road
b_img.dummy[11]	-0.273	Separated cycling lane	N/A	Residential
b_img.dummy[12]	-0.116	Solitary cycling lane	N/A	Main road
b_img.dummy[13]	-0.046	Solitary cycling lane	N/A	Residential
b_img.dummy[14]	0	Solitary cycling lane	N/A	Recreational

Table 3: Prior beta parameters. Adapted from Significance, 2022

4.4.3 Survey design and implementation

After the generation of the efficient design, a random selection of images from a specific category has been incorporated into the design. To illustrate, if alt1.image is 14, a random image from category 14 has been included. In order to prevent the machine learning model from over-fitting the data, it is necessary to split the data set into a training set and a test set (Muraina, 2022). Firstly, each respondent is randomly assigned among these sets, comprising 80% and 20% of the total respectively. Secondly, the image category is randomly assigned among these sets. Respondents from the training set will only see images from the training set, and vice versa. The train set is used for training the model; the test is unknown to the model during training and is used to evaluate the performance of the model. If the trained model overfits the data, a difference in performance between the training and testing sets will be seen (Cranenburgh and Garrido-Valenzuela, 2023).

As previously indicated the efficient design comprises thirty choice situations, which is done to maintain attribute balance. However, it is unreasonable to expect respondents to engage in thirty choice situations. Hence, two design blocks of fifteen choice situations are created. Firstly, the design block number (1 or 2) was randomly assigned to each respondent. Secondly, the order of the choice questions was randomised for each respondent. Thirdly, the order of the left/right alternatives as defined in the underlying design was randomised within and between respondents. Lastly, it was guaranteed that respondents would not see the same image more than once during the first part of of the survey.

In collaboration with Francisco Garrido-Valenzuela (Garrido-Valenzuela, 2024) a website was developed for the survey using Python Dash (Plotly, 2024). The survey consists of three parts: 1) fifteen choice situations, in which participants have to select their preferred route for each; 2) five image rating questions, based on images seen previously on traffic safety, social safety and beauty; and 3) socio-demographic information and questions about cycling. The link to the survey is: http://cycling-route-survey.tbm.tudelft.nl/.

4.4.4 Survey layout

Respondents were asked to compare two different cycling routes and to choose the one they would cycle. When replying to each question, they had to consider the following:

- Imagine you are cycling from your work, train station, school, or daily activity to your home.
- There are two cycling routes you can take.
- The routes differ only in **travel time**, the number of **traffic lights**, and the **cycling environment** shown in the photo.
- In all other aspects, such as the weather, the cycling routes are the same.
- **Which route would you choose?**
- You can assume the following:
  - You are cycling alone.
  - You are not in a hurry.
  - The photo gives a good idea of what the **entire route** looks like.
  - The travel time is the **total time** for the route, **including waiting at traffic lights.**
  - The weather is partly cloudy with no rain.

Figure 3 provides an example of a visual representation of the survey layout.

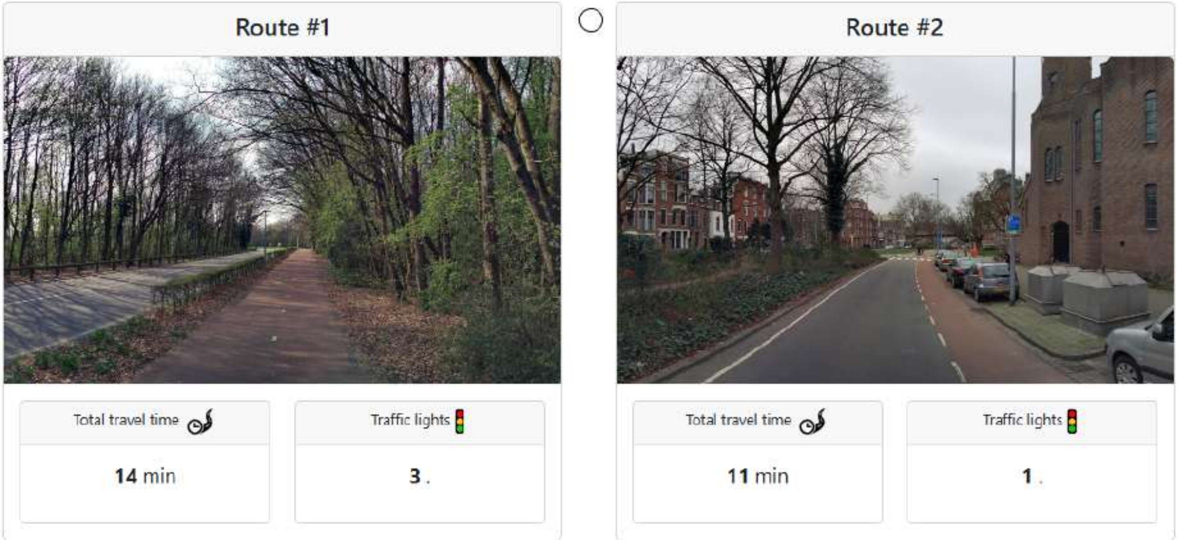


Figure 3: Example of a choice situation

4.4.5 Descriptives of the respondents

The survey was completed by 753 individuals through the panel company Cint (2024) between the end of September and the beginning of October 2024. The respondents were financially compensated for their participation in the survey. The respondents in the study were individuals aged 18 years and above who engage in cycling. Individuals who do not cycle were unable to participate in the survey, as it is focused on cycling routes. An effort was made to ensure that the sample was representative of the Dutch population. This was achieved by filtering the data in advance based on gender, age, and region through the data of CBS (2024a). Additionally, individuals who completed the survey so quickly (half of the questions within three seconds) that it was not possible to actually make a choice based on the attributes were filtered out.

4.4.6 Images applied in the survey

The image database contains approximately 13.000 images which are classified into fifteen categories. The category with the lowest number of images includes 149 images, suggesting a high probability of image repetition. This probability varies across categories, with some categories having a higher probability than others. A total of 6.484 unique images were applied in the survey. Approximately 2.000 images were used once. One image was observed to have been shown 23 times, representing the highest frequency.

4.5 Training the cv-dcm

In order to train the cv-dcm, a pre-trained model was applied to reduce both the computational time and the data requirements. Transfer learning was used to start with a model that had already learned relevant visual features, thereby providing a good foundation. In particular, the DeiT base model (Touvron et al., 2021) was employed, which had been pre-trained on ImageNet (2024), a comprehensive dataset comprising 1.2 million images. This approach allowed for the beginning of training from an already effective starting point, thereby ensuring both efficiency and model performance. The images now consist of a feature map of 1000 values, which contains most of the information that can be seen in the image and will be used for training the cv-dcm. The values of the feature map are converted to a normal distribution with the mean zero and the standard deviation 0.1.

4.5.1 Cross-entropy loss function

The feature map, combined with the numeric attributes, was estimated similarly to a classical discrete choice model, as described in Chapter 5.2. The primary goal was to identify the beta parameters for travel time, traffic lights, and the 1,000 elements of the feature map that would minimise the cross-entropy loss. The cross-entropy loss function aims to reduce the error between the actual and predicted outcomes (DataCamp, 2024), with a lower cross-entropy value indicating improved model performance. Minimising this loss is effectively equivalent to maximizing the log-likelihood (LL). The cross-entropy loss function is presented in Formula 5. The second part of the formula is the L2 regularisation. The purpose of the L2 regularisation is to help prevent the model from overfitting by adding a penalty based on the size of the model's weights. The strength of this penalty is controlled by the parameter . The regularisation is only applied to the feature extractor weights w and not to the preference parameters β_m and β_k. Regularising these preference parameters could potentially introduce unwanted biases into the model (Cranenburgh and Garrido-Valenzuela, 2023).

$$w, \beta = \arg\min_{w,\beta} \left(\underbrace{\frac{1}{N} \sum_{n=1}^{N} \sum_{j=1}^{J} y_{nj} \log(P_{nj} | X_{nj}, S_{jn}, \beta) +}_{\text{Cross-entropy loss}} \quad \underbrace{\gamma \sum_{r=1}^{R} w_r^2}_{\text{L2 regularisation}} \right) \tag{5}$$

4.5.2 Training and hyperparameter tuning

The cv-dcm has been implemented and trained using PyTorch. This was done by Associate Professor Sander van Cranenburgh (van Cranenburgh, 2024). The methodology in this study is similar to that applied in the study of Cranenburgh and Garrido-Valenzuela (2023). PyTorch is a machine learning package that is frequently employed in the field of deep learning and computer vision research due to its ability to support GPU computing. The hyper parameters of the cv-dcm were determined through the utilisation of a heuristic search approach. A variety of optimisation algorithms, learning rates, batch sizes and regularisation settings have been tested in order to determine the optimal hyperparameters. A comprehensive hyperparameter tuning would have been the optimal approach, involving the testing of all possible combinations of optimisation algorithms, learning rates, batch sizes, and regularisation parameters. However, due to the high computational cost associated with training cv-dcm (and CV models in general), this was not a feasible option. Instead, the hyperparameters in Table 4 are identified as the most effective.

Hyperparameter	**Value**
Device	cuda
Optimisation algorithm	Stochastic Gradient Descent
Learning Rate	1×10^{-5}
Batch Size	5
L2 weight decay (γ)	0.1

Table 4: Hyperparameters for Model Training

5 Results

5.1 Parameter estimates

Different models were developed to predict cycling route choice. Model 1 predicts the data with only information about traffic lights and travel time. This model was applied as a benchmark to assess the degree of improvement in prediction accuracy of the cv-dcm. Model 2 is the cv-dcm. The cv-dcm can accommodate choice tasks involving numeric attributes and images. Model 3 was then estimated using the predicted utility scores for each image of the cv-dcm. This was done to ensure consistency in the training process, as the cv-dcm was trained with backpropagation, while the other models were trained with the bgw method. In order to facilitate a comparison of the models, the cv-dcm was also estimated using this bgw method, which is more precise than backpropagation. To analyse which attributes of the cycling environment are deemed important, model 4 was estimated, which predicts separate built environment characteristics and infrastructure elements. Subsequently, model 5 was estimated, incorporating both the cv-dcm score and the infrastructure and built environment. In order to prevent overfitting, a training and testing set was applied. The parameters were trained on the training set and subsequently validated on the test set. Table 5 illustrates the estimation results of the various models. Notably, the models did not overfit the data, as evidenced by the minimal differences in rho-square between the training and test sets. For each model, travel time is expressed in terms of traffic lights. It can be seen that one extra traffic light can be compared to about one and a half minutes.

Model Equations

$$\text{Model 1:} \quad U_{in} = \underbrace{\beta_{tt}\, tt_{in} + \beta_{tl}\, tl_{in}}_{\text{Utility } tt \text{ and } tl} + \varepsilon_{in} \tag{6}$$

$$\text{Model 2:} \quad U_{in} = \underbrace{\beta_{tt}\, tt_{in} + \beta_{tl}\, tl_{in}}_{\text{Utility } tt \text{ and } tl} + \underbrace{\sum_{k} \beta_{k} \cdot z_{ikn}}_{\textit{Utility image feature map}} + \varepsilon_{in} \tag{7}$$

$$\text{Model 3:} \quad U_{in} = \underbrace{\beta_{tt}\, tt_{in} + \beta_{tl}\, tl_{in}}_{\text{Utility } tt \text{ and } tl} + \underbrace{\beta_{s}\, s_{in}}_{\textit{Predicted utility score (cv-dcm)}} + \varepsilon_{in} \tag{8}$$

$$\text{Model 4:} \quad U_{in} = \underbrace{\beta_{tt}\, tt_{in} + \beta_{tl}\, tl_{in}}_{\text{Utility } tt \text{ and } tl} + \underbrace{\sum_{ce} \beta_{ce} \cdot ce_{in}}_{\textit{Utility cycling environment attributes}} + \varepsilon_{in} \tag{9}$$

$$\text{Model 5:} \quad U_{in} = \underbrace{\beta_{tt}\, tt_{in} + \beta_{tl}\, tl_{in}}_{\text{Utility from } tt \text{ and } tl} + \underbrace{\beta_{s}\, s_{in}}_{\textit{Predicted utility score (cv-dcm)}} + \underbrace{\sum_{ce} \beta_{ce} \cdot ce_{in}}_{\textit{Utility cycling environment attributes}} + \varepsilon_{in} \tag{10}$$

Model 1: Travel time and traffic lights
Model 1 with only travel time and traffic lights shows a relatively low rho-square of 0.036, indicating that the model explains only a minor proportion of the data.

Model 2: CV-DCM
It can be observed that the rho-square of the cv-dcm is 0.101. This value is considerably higher than that of Model 1. It can therefore be concluded that the cv-dcm is capable of accurately predicting the utility of the images, and that the cycling environment exerts a significant influence on cycling route choice behaviour. A rho-square of 0.101 is not very high, yet still within an acceptable range. The observed parameters align with expectations, particularly in regard to the disutility of travel time and traffic lights. In Chapter 5.2 the cv-dcm is analysed in detail.

Model 3: Environment score estimated with bgw
The rho-square value for Model 3 is 0.115. Furthermore, the BIC value of this model is the lowest. It was anticipated that the beta parameter of the score would be equal to 1, given that the score of an image was already represented in utility by the cv-dcm. The difference can be attributed to the different optimisation techniques applied for each model. The cv-dcm was trained with backpropagation, whereas the other models were optimised with bgw. It can be seen that Model 3 has a marginally higher rho-square than Model 2, suggesting that bgw can predict slightly more precise. In contrast, the computation time of backpropagation is way much shorter.

Model 4: Cycling environment attributes
Model 4 predicts the data based on the variables of travel time, traffic lights, infrastructure characteristics, the built environment, and weather. Rho-sqaure is 0.092, so the model does not outperform the cv-dcm. The cv-dcm highlights the significance of the cycling environment as a factor influencing individuals' decisions. However, it does not provide insights of specific elements within the environment as it is based on a neural network. This model is particularly useful because this model allows to isolate the impact of each attribute on the cyclist's choice. For a detailed examination of the parameters associated with Model 4, please refer to Chapter 5.3.

Model 5: Cycling environment attributes and environment score
Lastly, the predicted scores derived from the images were integrated with Model 4. Although this method yields the highest rho-squared, the BIC value is higher than that of the cv-dcm. Furthermore, it can be seen that numerous parameters in Model 4 have become insignificant. This is in accordance with expectations, given that the image score contains data about the built environment and infrastructure elements. During the analysis, it was observed that only the parameter of industrial area is still very significant, thereby contributing additional information. This suggests that while the cv-dcm provides good utility score predictions overall, it has room for improvement specifically in predicting utility scores for industrial areas.

	Model 1			Model 2			Model 3			Model 4			Model 5		
Model type	RUM-MNL			CV-DCM			RUM-MNL			RUM-MNL			RUM-MNL		
Estimation method	bgw			backpropagation			bgw			bgw			bgw		
Number of parameters	2			86m			3			15			16		
Train Set (N = 9135)															
Log-Likelihood	-6157			-5656			-5590			-5704			-5529		
Rho-squared	0.028			0.109			0.117			0.099			0.127		
Cross-entropy	0.674			0.617			0.612			0.624			0.605		
BIC	12332			-			11600			11208			11204		
Test Set (N = 2128)															
Log-Likelihood	-1421			-1326			-1306			-1339			-1298		
Rho-squared	0.036			0.101			0.115			0.092			0.120		
Cross-entropy	0.668			0.623			0.614			0.629			0.610		
BIC	2857			-			2635			2793			2719		
	est	**s.e.**	**p-val**	**est**	**s.e.**	**p-val**	**est**	**s.e.**	**p-val**	**est**	**s.e.**	**p-val**	**est**	**s.e.**	**p-val**
Parameters															
β_{tt}	-0.11	0.012	0.00	-0.10			-0.21	0.013	0.00	-0.23	0.0139	0.00	-0.23	0.014	0.00
β_{tl}	-0.23	0.021	0.00	-0.24			-0.30	0.022	0.00	-0.31	0.0215	0.00	-0.32	0.022	0.00
$\beta_{utilityscore}$							1.17	0.052	0.00				0.98	0.059	0.00
$\beta_{normalroad}$										0.00	Fixed	Fixed	0.00	Fixed	Fixed
$\beta_{suggestionlane}$										-0.05	0.054	0.37	-0.10	0.055	0.07
$\beta_{separatedlane}$										0.36	0.054	0.00	0.14	0.056	0.01
$\beta_{klinkers}$										-0.11	0.041	0.01	-0.05	0.043	0.25
β_{sunny}										0.09	0.033	0.01	0.04	0.034	0.22
$\beta_{brightness}$										0.04	0.008	0.00	0.02	0.008	0.01
β_{trees}										0.10	0.015	0.00	0.04	0.016	0.01
β_{water}										0.18	0.038	0.00	0.08	0.039	0.03
β_{house}										-0.31	0.049	0.00	-0.14	0.049	0.01
$\beta_{industrial}$										-0.63	0.059	0.00	-0.47	0.062	0.00
β_{gras}										0.24	0.038	0.00	-0.01	0.040	0.85
$\beta_{parking}$										-0.09	0.039	0.02	0.12	0.040	0.00
β_{tram}										-0.23	0.107	0.03	-0.19	0.107	0.07
β_{plants}										0.03	0.037	0.45	-0.05	0.038	0.17
Value of time	2.12	0.2522	0.00	2.38			1.43	0.1163	0.00	1.38	0.1034	0.00	1.39	0.104	0.00

Table 5: Model Comparison Table

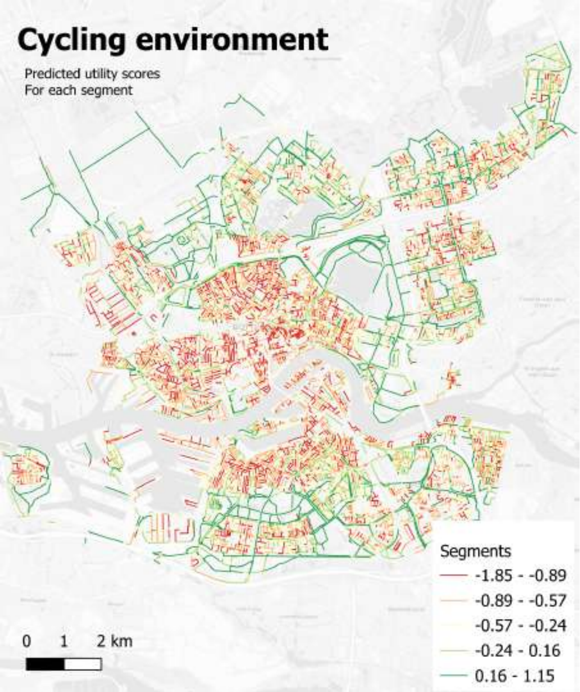
5.2 Results of the cv-dcm (Model 2)

Section 5.1 demonstrated that the cv-dcm is capable of accurately predicting utilities for cycling environments based on images. Building on this, the objective of analysing the cv-dcm is to gain insight into the types of environments in which individuals prefer to cycle, as well as those in which they do not, as reflected in the utility scores assigned by the cv-dcm.

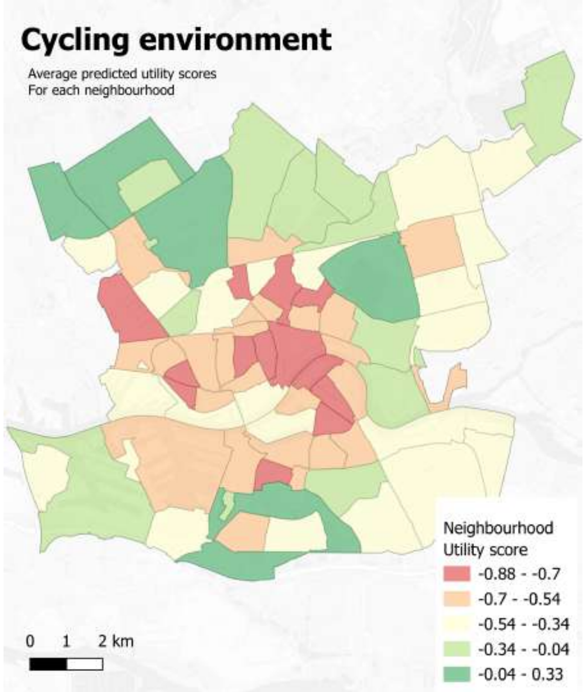
The cv-dcm is applied to the dataset, consisting of 13.000 images and representing the entire cycling network of Rotterdam. A predicted utility score is assigned to all images. The utility score itself is of limited value as it does not have a defined scale. However, the utility score is very valuable for identifying differences between images. These differences enable spatial, qualitative, and quantitative analyses and have potential practical applications. Additionally, utility differences are analysed in conjunction with travel time and traffic lights, providing insights into the trade-offs cyclists make when selecting routes. The utility score of the Rotterdam cycling network ranges from -1.85 to 1.15. The mean utility is -0.5. It should be noted that a negative score does not necessarily indicate a poor cycling environment.

5.2.1 Spatial distribution

The utility scores were plotted on a map of Rotterdam. The scores are divided into 5 clusters using the Jenks natural breaks method (J. Chen et al., 2013). Figure 4a illustrates the utility score cluster for each cycling segment. Figure 4b illustrates the mean utility score cluster for each neighbourhood. It is notable that the centre of Rotterdam is coloured red and orange, while the surrounding regions are coloured yellow and light green. The recreational areas Kralingse Plas, Zuiderpark, Park Zestienhoven and an area to the upper left, which is mostly composed of meadows, are represented by a dark green colour. This contrast suggests that people may find green spaces and less densely areas more enjoyable for cycling than densely populated urban areas.



(a) Utility scores for each segment



(b) Average utility score per neighbourhood

Figure 4: Predicted utility scores on the map

5.2.2 Visual representation of high and low utility scores

Figure 5 displays nine random images from the highest and lowest cluster. It is very noticeable that the images with high scores consist mainly of separated cycling lanes located in environments with trees, grass, and a minimal presence of buildings or cars. In contrast, images with low scores are located in urbanised environments with numerous buildings, vehicles, and narrow roads shared with other traffic. This analysis demonstrates a clear relationship between attributes such as greenery, cars, building density, and cycling infrastructure, and their impact on the cv-dcm utility scores. These results are consistent with the literature and hypotheses. Individuals tend to favour cycling in an environment characterised by a high degree of greenery (P. Chen et al., 2018). Additionally, cycling lanes where cyclists are separated from other traffic are preferred above no cycling lane (Rossetti et al., 2018).

(a) Cluster 1 (0.16 to 1.15 utility)

(b) Cluster 5 (-1.85 to -0.89 utility)

Figure 5: Low and high utility scores

5.2.3 Impact of cycling infrastructure on utility scores

The preceding qualitative analysis provided a general view of how perceived cycling experience varies across different cycling environments. In contrast, this section delves deeper into the role of cycling infrastructure in shaping cycling preferences.

Previous studies suggest that cyclists prefer separated cycling lanes over shared lanes with motorised traffic (Kaplan and Prato, 2015; Rossetti et al., 2018; Significance, 2022), with Rossetti et al. (2018) showing this preference using a stated choice experiment with generated images. However, GPS-based studies found cyclists to be less sensitive to infrastructure differences (Bernardi et al., 2018; Ton et al., 2017), indicating that it is context dependent. Higher vehicle speeds negatively affect route choices, especially when cyclists share the road with traffic, with cycling rates dropping at speeds over 30 km/h (Jestico et al., 2016; Verhoeven et al., 2018; Winters et al., 2013).

This study uses real-world images and the cv-dcm to assess how infrastructure affects utility scores. Figure 6 shows that separated and solitary cycling lanes have higher utility scores than normal roads and suggestion lanes, with suggestion lanes scoring higher than normal roads. The substantial difference in utility between separated lanes and suggestion lanes highlights the importance of constructing separated cycling lanes to improve cycling experiences. The figure also shows no significant difference in utility scores for 30 km/h versus 50 km/h roads, likely because speed information was not explicitly provided in the survey, and participants may not have inferred it from the images. While speed appears insignificant in this study, it may still play a role in real-world route choices.

The difference in median utility between normal roads and separated cycling lanes is around 0.8. Given a beta parameter for travel time of 0.11, cyclists are willing to travel 8 minutes longer to use a separated lane for an 11-minute trip. However, since built environment factors were not controlled, this effect may be overestimated.

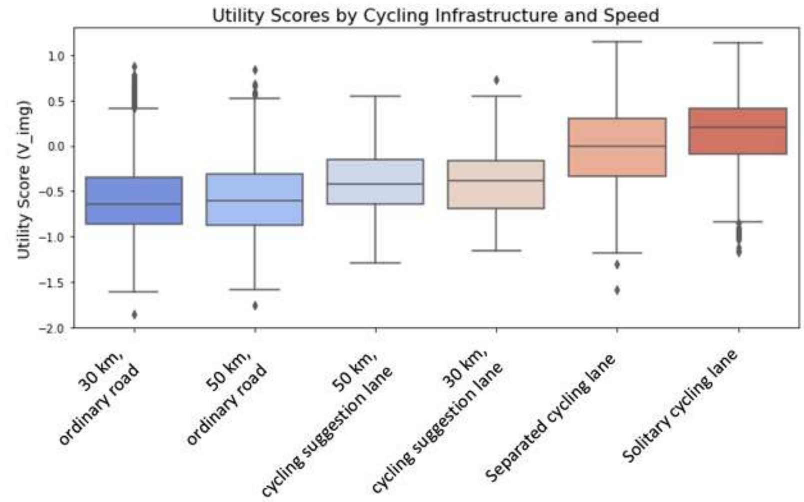


Figure 6: Utility scores by cycling infrastructure

5.2.4 Practical applications

The municipality of Rotterdam is taking steps to encourage more people to cycle and to improve cyclists' comfort and sense of safety. Recent renovations on the cycling infrastructure have been implemented; however, quantifying their impact remains challenging. Evaluations after such renovations are frequently absent, which limits the ability to assess the effectiveness of these renovations. The application of the cv-dcm offers a promising solution to this issue. By comparing the difference in predicted utility scores, the extent to which cyclists value the improvements of the infrastructure can be analysed. This data-driven evaluation can also inform future decision-making, ensuring that investments in cycling infrastructure align with cyclists' preferences and contribute to a safer and more comfortable cycling environment.

Walenburgerweg
The Walenburgerweg is a busy neighbourhood access road in the Provenierswijk, Rotterdam North. In 2023, the cycling lane was widened and painted red. Further, the speed limit was modified from 50 km/h to 30 km/h. Although, this is not really noticeable from the images. Figure 7 illustrates the pre- and post-intervention conditions. Furthermore, the number of cars in the image, the weather conditions and the lighting are almost identical.

The image taken prior to the renovation is rated with a utility score of -0.77. The image taken after the renovation is rated with a utility score of -0.27. This represents a difference in utility of 0.5, indicating that the combination of widening the cycling lane and the red colour is preferred by cyclists. The beta parameter of travel time is -0.11, indicating that people are willing to cycle for an additional five minutes on the new cycle infrastructure rather than the old cycle infrastructure for a cycle trip of approximately 11 minutes.

From this case study, it is demonstrated that the cv-dcm identifies a difference in perceived cycling experience when cycling infrastructure has been improved. This indicates that the cv-dcm is capable of accurately estimating how the cycling infrastructure is perceived by cyclists, which is a valuable tool for the municipality to evaluate the impact of cycling infrastructure renovations, such as lane widening and colour changes. Applying the cv-dcm across renovation projects supports data-driven decision-making, which in turn can contribute to cyclist-friendly environments.

Figure 7: Case study of the Walenburgerweg in Rotterdam

5.3 Impact of environmental attributes on cycling route choices (Model 4)

The cycling environment attributes model (Model 4 in Table 5) is analysed in this chapter. This model is estimated to identify the environmental attributes that influence cycling route choices. It is particularly useful because this model allows to isolate the impact of each attribute on the cyclist's choice. So now clear insights into which attributes are most influential are gained.

Table 5 shows that most parameters have p-values below 0.05 indicating that the parameters are significant at 5% level. Figure 8 illustrates the impact of the significant attributes on the utility. It can be observed that the presence of a separated cycling lane, trees, grass, water, and sun have a positive influence on cycle route choice, whereas the presence of car parking, clinkers (instead of asphalt), a tram on the road, houses, and industrial areas have a negative influence. These findings align with the cv-dcm and the expectations. It highlights the significant influence of the built environment and cycling infrastructure type on cyclists' route preferences. Green, scenic surroundings and dedicated cycling infrastructure are strongly associated with greater cyclist preference for routes, while urban features negatively impact route choice. This demonstrates the necessity for policy to prioritise green and separated cycling lanes, with the aim of encouraging cycling and enhancing the overall experience.

It can be observed that the utility value increases by 0.38 when a separated cycling lane is present. This environment variable exerts the greatest positive influence on cycling route choice. The beta parameter for travel time is -0.23. This indicates that, on average, cyclists are willing to detour by 1.5 minutes for a separated cycling lane on an 11-minute trip.

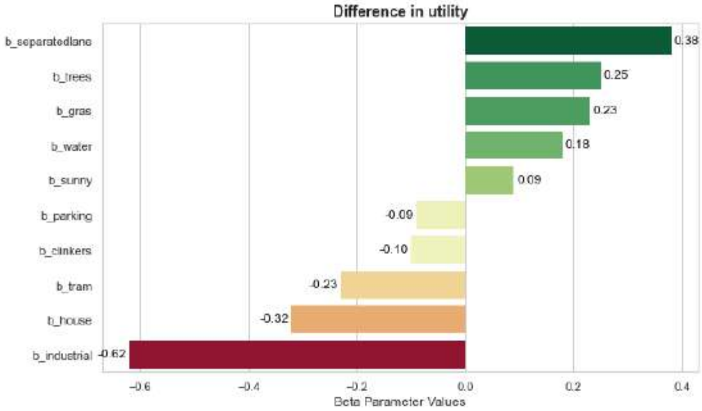


Figure 8: Difference in utility (based on Model 4)

6 Conclusions

This research contributes to the field of processing images into discrete choice models, where images are analysed using computer vision techniques. The relatively new model proposed by van Cranenburgh and Garrido-Valenzuela, known as cv-dcm, has been applied to understand cycling route choice behaviour. This model is capable of predicting choice behaviour based on both numerical attributes and images.

6.1 Scientific contributions

Notably, this is the first study that investigates cycling route choice behaviour using a large dataset of 6,500 unique street-level images in the stated choice experiment. The cv-dcm effectively predicts cycling route choice preferences, providing novel insights into the impact of cycling environments on decision-making. This approach provides a more realistic choice context compared to the majority of the current research, which relies on generated images or text-based descriptions.

This study builds on the prior cv-dcm application of Cranenburgh and Garrido-Valenzuela (2023) by introducing three key innovations: the pre-experiment image analysis, the use of an efficient design and a comprehensive data collection. The pre-experiment image analysis ensured that all characteristics of different cycling environments were visible in the images. Consequently, the model was able to effectively predict all different cycling environments. Furthermore, the image analysis facilitated the establishment of a ranking of the images, allowing for the utilisation of an efficient design, which is typically more advantageous than other designs. This approach improves trade-off insights and reduces parameter standard errors. The combination of an efficient design with a substantial quantity of real images for the prediction of choice behaviour represents a novel approach.

The cv-dcm relies on a neural network, which can make interpretability challenging. This study has addressed this by conducting a comprehensive data collection to represent the cycling environment with interpretable parameters. This allowed for a detailed examination of parameter influences on predicted utility scores of the cv-dcm and facilitated cycling route choice estimations using a traditional discrete choice model. This analysis has facilitated a clearer understanding of the influence of interpretable attributes on cycling route choice, bridging the gap between neural network models and classical DCMs.

6.2 Conclusions regarding cycling route behaviour

The results demonstrate that the cv-dcm outperforms traditional discrete choice models by effectively capturing image-based attributes that influence cycling route choice. This approach provides valuable insights into how cyclists perceive different cycling environments. The cycling environment is perceived as more influential than travel time and traffic lights in route choice decisions, highlighting its crucial role in cyclists' preferences. Additionally, the cv-dcm revealed that green and open environments with separated cycling lanes are highly valued by cyclists, while urbanised areas with mixed-traffic roads or industrial surroundings are less preferred. The cv-dcm also effectively identifies differences in utility between cycling infrastructure characteristics, such as type, width and colour. This can be very valuable as practical application to evaluate the impact of cycling infrastructure renovations on perceived cycling experience. The discrete choice model provided insights by isolating the effects of specific attributes on route choice. Positive influences on route choice include separated cycling lanes, greenery, and water, while car parking, houses, clinker pavement, tram lines, and industrial areas have negative impacts. Notably, on average, cyclists are willing to take a detour of approximately 1.5 minutes to cycle on a separated cycling lane instead of mixed-traffic roads for a cycle trip of approximately 11 minutes.

7 Discussion

This section critically discusses uncertainties and results that have been presented throughout this paper. The high importance of the environment may also be attributed to the manner in which the data was presented to respondents. The environment was displayed through images, whereas travel time and traffic lights were represented as numeric attributes. Research has demonstrated that images are more effective at capturing attention than numeric attributes (Murwirapachena and Dikgang, 2022). Another limitation of stated choice experiments is the potential differences between individuals' stated preferences and their actual preferences (Wardman, 1988). Without experiencing the route in reality, respondents may misjudge factors like travel time or overvalue the environment.

An actual cycle route is comprised of numerous segments, each with different characteristics that collectively influence the cycling experience. In the study, to maintain simplicity for respondents, one image was selected per cycle route. A single image may not fully capture real-world cycling routes, potentially limiting the realism of the choice situations.

The cv-dcm scores are not explained easily by interpretable parameters. Unlike traditional discrete choice models, where parameters provide clear and quantifiable insights into decision-making, the cv-dcm relies on features extracted from images through a deep neural network. This limits the model's applicability for the municipality who require transparent and actionable insights.

8 Recommendations

From this research, there are several aspects that can be further explored to gain better understanding of the working of the cv-dcm and cycling routes.

This study applied a stated choice experiment. To validate whether cyclists prioritise the environment to the same extent in real-world scenarios, it would be valuable to compare this research with revealed preference. One potential method is to analyse Strava or GPS data, which captures actual cycling routes and behaviour. By examining how cyclists navigate through a city using revealed preferences, it could be explored whether environmental factors such as greenery, separated cycling lanes, and road quality significantly influence route choices in reality.

The cv-dcm represents a significant advancement in choice modelling, as it is the first model that incorporates images into choice situations. To further improve the realism of choice situations, it is recommended to incorporate multiple images or videos which simulate the dynamic nature of cycling routes. The potential of virtual reality could also be explored, allowing participants to experience routes in a more realistic manner. Additionally, sensory factors such as noise and smell could be integrated to capture the full experience. This approach enables participants to make choices in a highly realistic environment, offering deeper insights into how factors such as greenery, traffic noise, and cycling infrastructure influence route preferences.

To improve the interpretability of the cv-dcm, future research could explore the application of Explainable AI (XAI) techniques such as SHAP (Shapley Values) or LIME (Local Interpretable Model-Agnostic Explanations). Building on previous research of Bakker (2024), integrating LIME with object detection may offer a more precise understanding of the visual elements influencing utility scores. These methods could provide insights into how specific attributes, like lane width, trees, or the presence of parked cars, influence individual cycling environment scores. Such insights could support targeted interventions to improve low-scoring areas.

The potential to apply the cv-dcm model in the formulation of policy, rather than in its evaluation, represents another avenue for further research. For instance, if a road is found to be not attractive for cyclists and the municipality want to improve its cycling infrastructure, ai-driven image editing models could be used to generate a range of potential future designs. These designs could then be evaluated by the cv-dcm to determine perceived cycling experience. This, in turn, provides the opportunity to make trade-offs between cost and cycling environment when considering improvements to cycling infrastructure.

References

Bakker, B. (2024). *Leveraging lime for human-understandable explanations in urban computer vision models* [Master's thesis, Delft University of Technology]. http://resolver.tudelft.nl/uuid:6cfbd82f-dd12-4593-87e2-83726053dbfc

Bernardi, S., La Paix-Puello, L., & Geurs, K. (2018). Modelling route choice of dutch cyclists using smartphone data. *Journal of Transport and Land Use*, *11*(1). https://doi.org/10.5198/jtlu.2018.1143

Berry, W. D. (1985). *Multiple regression in practice*. Sage.

BGT. (2024). Basisregistratie grootschalige topografie. https://www.kadaster.nl/zakelijk/registraties/basisregistraties/bgt

CBS. (2024a). Cbs. https://opendata.cbs.nl/statline/#/CBS/nl/

CBS. (2024b). Statistieken woonplaats rotterdam. https://allecijfers.nl/woonplaats/rotterdam/

Chen, J., Yang, S. T., Li, H. W., Zhang, B., & Lv, J. R. (2013). Research on geographical environment unit division based on the method of natural breaks (jenks). *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *XL-4/W3*, 47–50. https://doi.org/10.5194/isprsarchives-XL-4-W3-47-2013

Chen, P., Shen, Q., & Childress, S. (2018). A gps data-based analysis of built environment influences on bicyclist route preferences. *International Journal of Sustainable Transportation*, *12*(3), 218–231. https://doi.org/10.1080/15568318.2017.1349222

ChoiceMetrics. (2024). Ngene. https://choice-metrics.com/download.html

Cint. (2024). Cint. https://www.cint.com/

Columbiauniversity. (2020). Discrete choice model and analysis. https://www.publichealth.columbia.edu/research/population-health-methods/discrete-choice-model-and-analysis

Cranenburgh, S., & Garrido-Valenzuela, F. (2023). Computer vision-enriched discrete choice models, with an application to residential location choice.

Cyclomedia. (2023). Panoramafoto's rotterdam actueel. https://www.gis.rotterdam.nl/gisweb2/default.aspx

DataCamp. (2024). Cross-entropy loss function in machine learning. https://www.datacamp.com/tutorial/the-cross-entropy-loss-function-in-machine-learning

Donath, C., Gräßel, E., Baier, D., Pfeiffer, C., Bleich, S., & Hillemacher, T. (2012). Predictors of binge drinking in adolescents: Ultimate and distal factors - a representative study. *BMC Public Health*, *12*(1), 263. https://doi.org/10.1186/1471-2458-12-263

Dubey, A., Naik, N., Parikh, D., Raskar, R., & Hidalgo, C. A. (2016). Deep learning the city: Quantifying urban perception at a global scale. In B. Leibe, J. Matas, N. Sebe, & M. Welling (Eds.), *Computer vision – eccv 2016* (pp. 196–212). Springer International Publishing.

Dutch Cycling Embassy. (2018). Dutch cycling vision. https://dutchcycling.nl/wp-content/uploads/2022/05/Dutch_Cycling_Vision_EN.pdf

Elu, A., Azkune, G., de Lacalle, O. L., Arganda-Carreras, I., Soroa, A., & Agirre, E. (2021). Inferring spatial relations from textual descriptions of images. *CoRR*, *abs/2102.00997*. https://arxiv.org/abs/2102.00997

European Union. (2023). The importance of active mobility in the face of climate change. https://www.euroclima.org/en/recent-events-urban/articles-and-interviews/1981-world-bike-day-the-importance-of-active-mobility-in-the-face-of-climate-change

Fietsersbond. (2020). Data fietsersbond. https://www.fietsersbond.nl/

Garrido-Valenzuela, F. (2024). Staff profile: Francisco garrido-valenzuela, tu delft [Accessed: 2024-11-10]. https://www.tudelft.nl/en/staff/f.garridov/?cHash=9e453a8f8a6dcb0026be2a7f9f604398

Gemeente Rotterdam. (2019a). Fietskoers 2025. https://www.rotterdam.nl/fietsstad

Gemeente Rotterdam. (2019b). Veilig op pad. https://www.rotterdam.nl/veilig-op-pad

Gemeente Rotterdam. (2023). Verkeersveiligheidsprikker. https://www.rotterdam.nl/verkeersveiligheidsprikker

Gössling, S., & McRae, S. (2022). Subjectively safe cycling infrastructure: New insights for urban designs. *Journal of Transport Geography*, *101*, 103340. https://doi.org/https://doi.org/10.1016/j.jtrangeo.2022.103340

Heinen, E., van Wee, B., & Maat, K. (2010). Commuting by bicycle: An overview of the literature. *Transport Reviews*, *30*(1), 59–96. https://doi.org/10.1080/01441640903187001

ImageNet. (2024). Imagenet. https://image-net.org/index.php

Ito, K., & Biljecki, F. (2021). Assessing bikeability with street view imagery and computer vision. *Transportation Research Part C: Emerging Technologies*, *132*, 103371. https://doi.org/https://doi.org/10.1016/j.trc.2021.103371

I&W. (2020). Klimaatbeleid. https://www.rijksoverheid.nl/onderwerpen/klimaatverandering/klimaatbeleid
Jestico, B., Nelson, T., & Winters, M. (2016). Mapping ridership using crowdsourced cycling data. *Journal of Transport Geography*, *52*, 90–97. https://doi.org/https://doi.org/10.1016/j.jtrangeo.2016.03.006
Juarez, R. N. R., Grigolon, A. B., & Madureira, A. M. (2023). Cyclists' perception of streetscape and its influence on route choice: A pilot study with a mixed-methods approach. *Transportation Research Part F: Traffic Psychology and Behaviour*. https://api.semanticscholar.org/CorpusID:265005257
Kaplan, S., & Prato, C. (2015). A spatial analysis of land use and network effects on frequency and severity of cyclist-motorist crashes in the copenhagen region. *Traffic Injury Prevention*, *16*(7), 724–731.
KiM. (2023). Mobiliteitsbeeld 2023. https://www.kimnet.nl/publicaties/publicaties/2023/11/14/mobiliteitsbeeld-2023
Ma, X., Ma, C., Wu, C., Xi, Y., Yang, R., Peng, N., Zhang, C., & Ren, F. (2021). Measuring human perceptions of streetscapes to better inform urban renewal: A perspective of scene semantic parsing. *Cities*, *110*, 103086. https://doi.org/https://doi.org/10.1016/j.cities.2020.103086
McFadden, D. (1974). The measurement of urban travel demand. *Journal of Public Economics*, *3*(4), 303–328. https://doi.org/https://doi.org/10.1016/0047-2727(74)90003-6
Misra, A., & Watkins, K. (2018). Modeling cyclist route choice using revealed preference data: An age and gender perspective. *Transportation Research Record: Journal of the Transportation Research Board*, *2672*, 036119811879896. https://doi.org/10.1177/0361198118798968
Molin, D. E. J. (2024). Sen1221 statistical analysis of choice behaviour. https://brightspace.tudelft.nl/d2l/le/content/597386/Home
Muraina, I. (2022). Ideal dataset splitting ratios in machine learning algorithms: General concerns for data scientists and data analysts. *7th International Mardin Artuklu Scientific Research Conference*, 496–504.
Murwirapachena, G., & Dikgang, J. (2022). The effects of presentation formats in choice experiments. *Environmental Economics and Policy Studies*, *24*(3), 421–445. https://doi.org/10.1007/s10018-021-00328-4
Pan, X., Rasouli, S., & Timmermans, H. (2021). Investigating tourist destination choice: Effect of destination image from social network members. *Tourism Management*, *83*, 104217. https://doi.org/https://doi.org/10.1016/j.tourman.2020.104217
Plotly. (2024). Data apps for production. https://plotly.com/
Prato, C. (2009). Route choice modeling: Past, present and future research directions. *Journal of Choice Modelling*, *2*(1), 65–100. https://doi.org/https://doi.org/10.1016/S1755-5345(13)70005-8
QGIS. (2023). Qgis geographic information system. *QGIS Association*. https://www.qgis.org
Rose, J. M., & Bliemer, M. C. J. (2009). Constructing efficient stated choice experimental designs. *Transport Reviews*, *29*(5), 587–617. https://doi.org/10.1080/01441640902827623
Rossetti, T., Guevara, A., Galilea, P., & Hurtubia, R. (2018). Modeling safety as a perceptual latent variable to assess cycling infrastructure. *Transportation Research Part A: Policy and Practice*, *111*, 252–265. https://doi.org/https://doi.org/10.1016/j.tra.2018.03.019
Rossetti, T., Lobel, H., Rocco, V., & Hurtubia, R. (2019). Explaining subjective perceptions of public spaces as a function of the built environment: A massive data approach. *Landscape and Urban Planning*, *181*, 169–178. https://doi.org/https://doi.org/10.1016/j.landurbplan.2018.09.020
Sifringer, B., Lurkin, V., & Alahi, A. (2020). Enhancing discrete choice models with representation learning. *Transportation Research Part B: Methodological*, *140*, 236–261. https://doi.org/https://doi.org/10.1016/j.trb.2020.08.006
Significance. (2022). Values of time, reliability and comfort in the netherlands 2022. https://english.kimnet.nl/publications/publications/2024/04/03/new-values-of-travel-time-reliability-and-comfort-in-the-netherlands
Ton, D., Cats, O., Duives, D., & Hoogendoorn, S. (2017). How do people cycle in amsterdam? estimating cyclists' route choice determinants using gps data from an urban area. *Transportation Research Record: Journal of the Transportation Research Board*, *2662*, 1–10. https://doi.org/10.3141/2662-09
Touvron, H., Cord, M., Douze, M., Massa, F., Sablayrolles, A., & Jégou, H. (2021). Training data-efficient image transformers distillation through attention. https://arxiv.org/abs/2012.12877
van Cranenburgh, S. (2024). Staff profile: S. van cranenburgh, tu delft. https://www.tudelft.nl/staff/s.vancranenburgh/?cHash=0b1102c6a8de488000dd4cd02794b2a3
Verhoeven, H., Van Hecke, L., & Dyck, V. (2018). Differences in physical environmental characteristics between adolescents' actual and shortest cycling routes: A study using a google street view-based audit. *International Journal of Health Geographics*, *17*. https://doi.org/https://doi.org/10.1186/s12942-018-0136-x
Vidal-Tortosa, E., & Lovelace, R. (2024). Road lighting and cycling: A review of the academic literature and policy guidelines. *Journal of Cycling and Micromobility Research*, *2*, 100008. https://doi.org/https://doi.org/10.1016/j.jcmr.2023.100008
Visual Crossing. (2024). Weather data. https://www.visualcrossing.com/

Walker, J. L., Wang, Y., Thorhauge, M., & Ben-Akiva, M. (2018). D-efficient or deficient? a robustness analysis of stated choice experimental designs. *Theory and Decision*, *84*(2), 215–238. https://doi.org/10.1007/s11238-017-9647-3

Wang, Y., Chau, C. K., Ng, W. Y., & Leung, T. M. (2016). A review on the effects of physical built environment attributes on enhancing walking and cycling activity levels within residential neighborhoods. *Cities*, *50*, 1–15. https://doi.org/https://doi.org/10.1016/j.cities.2015.08.004

Wardman, M. (1988). A comparison of revealed preference and stated preference models of travel behaviour. *Journal of Transport Economics and Policy*, *22*(1), 71–91. Retrieved November 18, 2024, from http://www.jstor.org/stable/20052836

Winters, M., Brauer, M., Setton, E. M., & Teschke, K. (2013). Mapping bikeability: A spatial tool to support sustainable travel. *Environment and Planning B: Planning and Design*, *40*(5), 865–883. https://doi.org/10.1068/b38185

Yang, Y., Wu, X., Zhou, P., Gou, Z., & Lu, Y. (2019). Towards a cycling-friendly city: An updated review of the associations between built environment and cycling behaviors (2007–2017). *Journal of Transport Health*, *14*, 100613. https://doi.org/https://doi.org/10.1016/j.jth.2019.100613

Zeng, Q., Gong, Z., Wu, S., Zhuang, C., & Li, S. (2024). Measuring cyclists' subjective perceptions of the street riding environment using k-means smote-rf model and street view imagery. *International Journal of Applied Earth Observation and Geoinformation*, *128*, 103739. https://doi.org/https://doi.org/10.1016/j.jag.2024.103739

Zimmermann, M., Mai, T., & Frejinger, E. (2017). Bike route choice modeling using gps data without choice sets of paths. *Transportation Research Part C: Emerging Technologies*, *75*, 183–196. https://doi.org/https://doi.org/10.1016/j.trc.2016.12.009