The contribution of building characteristics to the stimulation of bicycle use in access trips to train stations

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Preface

After months of hard work I am proud to present my master thesis. This thesis is written to obtain my master degree in Construction Management and Engineering and concludes my studies at the Eindhoven University of Technology. The study aims to add to the knowledge about the transportation mode choice for the bicycle, particularly for access trips to train stations, and focuses on the influence of building characteristics and how these characteristics can contribute to bicycle-stimulating environments. I am grateful that during this project I got the opportunity to combine the knowledge and skills I obtained during both my bachelor degree in Architecture and my master degree in Construction Management and Engineering.

Various people have directly or indirectly contributed to this study. I would first of all like to thank my first supervisor dr. ing. Peter van der Waerden for his continuous support and professional guidance throughout the research. I would also like to thank dr. ir. Pauline van den Berg for her feedback and the valuable insights she has given me on the project. Furthermore, I would like to thank Zuid-Limburg Bereikbaar for the opportunity to distribute my survey among their panel and the respondents that filled out the survey, which provided useful data for my research.

Lastly, I want to thank my family and friends for their limitless and unconditional support, advice, and interest not only during my graduation project but throughout my entire studies. Without them, I would not have been able to accomplish this.

Machteld Sanders

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Summary

Over the past decades, car use has been increasing, significantly contributing to the emission of greenhouse gasses. To bring down the emission levels, the use of sustainable transportation modes such as public transport, cycling, and walking have been encouraged. One of the most underused modes of public transport is the train, while it is one of the most sustainable transportation modes and at the same time can cover large distances, which makes it a feasible alternative for the car.

An important part of a train journey is the access trip – the trip from a starting point to the train station. Research has found that improving access trips to train stations will increase the overall level of satisfaction of travelers with train journeys. When people's opinion of a train journey becomes more positive, they are more likely to change their transportation mode to the train. Multiple studies suggest the use of the bicycle as an alternative transportation mode to motorized vehicles for access trips to train stations. However, what seems to be missing in the literature is how buildings and their characteristics are related to the willingness to cycle. Research indicates that cyclists who travel to train stations appear to have different preferences for characteristics of the built environment than cyclists who are engaged in unimodal cycling trips. This leaves a knowledge gap for the effect of building characteristics on the willingness to cycle in access trips to the train station. The main focus of this research will therefore be on the contribution of the characteristics of buildings along the route to the train station on the willingness to cycle in access trips.

To identify building characteristics that potentially stimulate bicycle use, existing literature is reviewed. The literature review suggests that a perception of an environment is formed through building façades. Therefore, the characteristics derived from the literature are all present in or visible when looking at the façade. To examine the contribution of these characteristics, a stated preference experiment was executed where respondents are presented with a rating task. They were asked to evaluate different cycling environments on an ordinal five-point scale on how much the environment would stimulate them to cycle in general ('Cycling in General') and in particular to access the train station ('Cycling to Train Station'). Furthermore, they were asked to evaluate how attractive ('Attractiveness') and suitable for cyclists ('Bicycle-Suitability') they considered the environments, to additionally examine if the building characteristics affect the experience of the environment for cyclists. So in total there were four dependent variables in the experiment. In order to mimic an actual cycling trip, the choice was made to visualize the building characteristics using simulated environments. The attributes that were used in the experiment are 'Building Height' (the number of floors of the buildings), 'Building Type' (whether all buildings are historic, modern or a mix of the two types), 'Openness of Façade' (the size of the windows on the ground floor of the building), 'Front Garden' (the absence or presence and size of a front garden), 'Distance to Buildings' (the distance from the bicycle path to the buildings), and 'Activity of Ground Floor' (the amount of activity/traffic in the street),. The survey containing the stated preference experiment was distributed online among members of the 'Zuid-Limburg Bereikbaar'-panel, which provided 894 valid responses.

The data collected through the experiment on 'Cycling in General' and 'Cycling to Train Station' was analyzed using an Ordered Logit model. Both variables showed similar results: low-rise buildings, semi-open façades, the presence of a front garden, and little to moderate traffic

were found to stimulate cycling, whereas modern building types, closed façades, the absence of a front garden, and small distances between bicycle path and buildings discourage cycling. Because the results are so similar, only 'Cycling to Train Station' was analyzed in further detail. A Random Effects model indicated that there is heterogeneity in the dataset. With a Latent Class model two classes were identified based on preferences. Though the differences in the evaluations of the building characteristics by each group were not very distinct, it could be determined that for Class 1 the attributes that provide a spacious environment ('Distance to Buildings', 'Building Height', and 'Openness of Façade') are more determining in stimulating bicycle use. The main attribute that differentiates Class 2 from Class 1 is 'Building Type', which is significantly important for Class 2 and shows no significance for Class 1. Personal characteristics could be linked to membership of one of the classes. There is a higher probability for females, higher educated people, people who cycle more than 20 km per week, and people who live fairly close to the train station to be a member of Class 1.

The data regarding the experience of the environment based on attractiveness and bicycle-suitability of the environment was analyzed using a Multinomial Logistic Regression model. It was concluded that building characteristics also affect cyclists' experience of the environment. In general, the similar results were found as for the 'Cycling in General' and 'Cycling to Train Station'. Low-rise buildings, semi-open façades, the presence of a front garden, and little to moderate traffic were found to make the environment more attractive and more suitable for cyclists, whereas modern building types, closed façades, the absence of a front garden, and small distances between bicycle path and buildings make the environment less attractive and less suitable for cyclists. Furthermore, it was concluded that 'Building Height' and 'Openness of the Façade' are somewhat more relevant attributes for the attractiveness of the environment, whereas 'Distance to Buildings' and 'Activity of the Ground Floor' are more determining for the bicycle-suitability of the environment.

The general conclusion of the research into how building characteristics contribute to the willingness to cycle in access trips is that 'Distance to Buildings' contributes to the willingness to cycle to the largest extent relative to the other building characteristics when treating cyclists as a homogeneous group. This is followed by 'Building Height', 'Activity of the Ground Floor', 'Building Type', and 'Front Garden'. 'Openness of the Façade' contributes to the willingness to cycle to the smallest relative extent. When taking into account heterogeneity, there are differences in the order of contribution of the attributes between the different groups of respondents. So, policy makers should pay attention to the existence of heterogeneity in the groups of travelers. Architects and urban designers should identify the target group of the area they are designing for using the personal characteristics linked to the identified groups. Consequently, they can base their design on the building characteristics that stimulate of the majority of the target group to cycle and can create (environmental) designs that stimulate bicycle use. Lastly, the results of the contribution of the building characteristics and corresponding attribute levels to the willingness to cycle are a means for urban planners to evaluate existing cycling routes to train stations. When implementing the results of the research in practice, more people will be stimulated to cycle to the train station and consequently will be persuaded to use the train as a transportation mode instead of the car. This mode shift will reduce the greenhouse gas emission levels, traffic congestion, and parking demand for cars.

Samenvatting

De afgelopen decennia is het autogebruik blijven toenemen, wat aanzienlijk bijdraagt aan de uitstoot van broeikasgassen. Om de uitstoot terug te dringen moet het gebruik van duurzame vervoerswijzen zoals openbaar vervoer, fietsen en lopen worden aangemoedigd. Een van de meest onderbenutte vormen van openbaar vervoer is de trein, terwijl het een van de meest duurzame vervoerswijzen is en tegelijkertijd grote afstanden kan afleggen, wat het een geschikt alternatief maakt voor de auto.

Een belangrijk onderdeel van een treinreis is de toegangsreis - de reis van een vertrekpunt naar het treinstation. Uit onderzoek is gebleken dat een betere toegang tot het station de algemene tevredenheid over treinreizen doet toenemen. Wanneer mensen positiever oordelen over een treinreis, zullen ze eerder geneigd zijn te reizen met de trein. Meerdere studies suggereren het gebruik van de fiets als een alternatieve vervoerswijze voor gemotoriseerde voertuigen voor de toegangsreis naar treinstations. Wat echter lijkt te ontbreken in de literatuur is hoe gebouwen en hun kenmerken bijdragen aan de bereidheid om te fietsen. Onderzoek stelt dat fietsers die naar treinstations reizen andere voorkeuren lijken te hebben voor kenmerken van de bebouwde omgeving dan fietsers die de hele reis met de fiets maken. Hier bestaat een kenniskloof voor het effect van gebouwkenmerken op de fietsbereidheid in toegangsreizen naar het treinstation. De focus van dit onderzoek ligt daarom op de bijdrage van de kenmerken van gebouwen langs de route naar het treinstation aan de fietsbereidheid in toegangsreizen.

Om de gebouwkenmerken te identificeren die mogelijk fietsgebruik stimuleren is bestaande literatuur bestudeerd. Uit de literatuurstudie blijkt dat de perceptie van een omgeving wordt gevormd door de gevels van gebouwen. Daarom zijn de uit de literatuur afgeleide kenmerken allemaal aanwezig in of zichtbaar bij het kijken naar de gevel. Om de bijdrage van deze kenmerken te onderzoeken is een stated preference experiment uitgevoerd waarbij respondenten een beoordelingstaak kregen voorgelegd. Hen werd gevraagd om de verschillende fietsomgevingen op een ordinale vijf-punts schaal te beoordelen op de mate waarin de omgeving hen zou stimuleren om te fietsen in het algemeen (‘Fietsen in het Algemeen’) en naar het treinstation (‘Fietsen naar het Trein Station’). Verder werd hen gevraagd te evalueren hoe aantrekkelijk (‘Aantrekkelijkheid’) en geschikt voor fietsers (‘Fietsgeschiktheid’) ze de omgeving vonden, om aanvullend te onderzoeken of de gebouwkenmerken de beleving van de omgeving voor fietsers beïnvloeden. In totaal zijn er dus vier afhankelijk variabelen in het experiment. Om een werkelijke fietstocht na te bootsen, is de keuze gemaakt om de gebouwkenmerken te visualiseren met behulp van gesimuleerde omgevingen. De kenmerken die als onafhankelijke variabelen in het experiment zijn gebruikt zijn 'Gebouwhoogte' (het aantal verdiepingen in het gebouw), 'Gebouwtype' (of alle gebouwen historisch, modern, of een mix van de twee types zijn), 'Openheid van de Gevel' (de grootte van de ramen op de begane grond van het gebouw), 'Voortuin' (de aanwezigheid en grootte van een voortuin), 'Afstand tot Gebouwen' (de afstand van het fietspad tot de gebouwen), en 'Activiteit van de Begane Grond' (de hoeveelheid activiteit/verkeer in de straat). De enquête met het stated preference experiment is online verspreid onder de leden van het ‘Zuid-Limburg Bereikbaar’-panel, wat 894 bruikbare antwoorden heeft opgeleverd.

De data die via het experiment is verzameld over ‘Fietsen in het Algemeen’ en ‘Fietsen naar het Treinstation’ is geanalyseerd met behulp van een Ordered Logit model. Beide variabelen

lieten vergelijkbare resultaten zien: laagbouw, halfopen gevels, de aanwezigheid van een voortuin, en weinig tot matig verkeer stimuleren fietsgebruik, terwijl moderne gebouwen, gesloten gevels, de afwezigheid van een voortuin, en kleine afstanden tussen het fietspad en de gebouwen fietsgebruik ontmoedigen. Omdat de resultaten vergelijkbaar zijn, is alleen 'Fietsen naar Treinstation' verder in detail geanalyseerd. Een Random Effects model gaf aan dat er heterogeniteit in de dataset zit. Met een Latent Class model werden twee groepen geïdentificeerd of basis van voorkeuren. Hoewel de verschillen niet erg uitgesproken zijn, kon worden vastgesteld dat de attributen die leiden tot een ruime omgeving ('Afstand tot Gebouwen', 'Gebouwhoogte', en 'Openheid van de Gevel') meer bepalend zijn voor het stimuleren van het fietsgebruik voor Klasse 1. Het belangrijkste attribuut dat Klasse 2 onderscheidt van Klasse 1 is 'Gebouwtype', dat significant is voor Klasse 2 en niet significant voor Klasse 1. Persoonlijke kenmerken konden gelinkt worden aan het behoren tot een van de klassen. Vrouwen, hoger opgeleiden, mensen die meer dan 20 km per week fietsen, en mensen die vrij dicht bij het station wonen, hebben een grotere kans om in Klasse 1 te vallen.

De data over de beleving van de omgeving op basis van de aantrekkelijkheid en de geschiktheid voor fietsers van de omgeving is geanalyseerd met een Multinomial Logistic Regression model. Hieruit is geconcludeerd dat gebouwkenmerken ook bijdragen aan de beleving van de omgeving door fietsers. In het algemeen werden vergelijkbare resultaten gevonden als voor 'Fietsen in het Algemeen' en 'Fietsen naar het Trein Station'. Laagbouw, halfopen gevels, de aanwezigheid van een voortuin, en weinig tot matig verkeer maken een omgeving aantrekkelijker en meer geschikt voor fietsers, terwijl moderne gebouwen, gesloten gevels, de afwezigheid van een voortuin, en kleine afstanden tussen het fietspad en de gebouwen de omgeving minder aantrekkelijk en minder geschikt voor fietsen maken. Verder is geconcludeerd dat 'Gebouwhoogte' en 'Openheid van de Gevel' iets relevanter zijn voor de aantrekkelijkheid, en 'Afstand tot Gebouwen' en 'Activiteit van de Begane Grond' iets belangrijker zijn voor de geschiktheid van de omgeving voor fietsers.

De algemene conclusie van het onderzoek naar de bijdrage van gebouwkenmerken aan fietsbereidheid in toegangsreizen kan worden geconcludeerd dat 'Afstand tot Gebouwen' het sterkst bijdraagt aan fietsgebruik in toegangsreizen vergeleken met de andere gebouwkenmerken wanneer fietsers als een homogene groep worden beschouwd. Dit wordt gevolgd door 'Gebouwhoogte', 'Activiteit van de Begane Grond', 'Gebouwtype' en 'Voortuin'. De bijdrage van 'Openheid van de Gevel' op de fietsbereidheid is relatief gezien het kleinst. Wanneer rekening wordt gehouden met heterogeniteit zijn er verschillen tussen de groepen in de volgorde waarin de attributen bijdragen. Beleidsmakers moeten daarom aandacht besteden aan de heterogeniteit van de groepen. Architecten en stedenbouwkundig ontwerpers moeten de doelgroep van het gebied waarvoor zij ontwerpen identificeren aan de hand van de persoonlijke kenmerken die gelinkt zijn aan de geïdentificeerde groepen. Op die manier kunnen zij hun ontwerp baseren op de gebouwkenmerken die de meerderheid van de doelgroep stimuleren en kunnen zij ontwerpen maken die het fietsgebruik stimuleren. Tenslotte zijn de resultaten van de bijdrage van de gebouwkenmerken en de bijbehorende attribuutniveaus een hulpmiddel voor stedenbouwkundig planners om bestaande fietsroutes naar treinstations te evalueren. Wanneer de resultaten van het onderzoek in de praktijk gebruikt worden, zullen meer mensen worden gestimuleerd om met de fiets naar het station te reizen en als gevolg daarvan zullen ze worden overgehaald om de trein als vervoerswijze te gebruiken in plaats van de auto. Deze verschuiving in vervoerswijze zal de uitstoot van broeikasgassen, verkeersopstoppingen, en de parkeervraag voor auto's verminderen.

Abstract

Over the past decades, car use has been increasing, significantly contributing to the emission of greenhouse gasses. To bring the emission levels down, train use has to be encouraged. An important part of a train journey is the access trip. Better access trips to train stations will increase the overall level of satisfaction with train journeys. The bicycle is a sustainable alternative transport mode for access trips to train stations. However, what seems to be missing in the literature is how buildings and their characteristics are related to the willingness to cycle. Research indicates that cyclists who travel to train stations appear to have different preferences for characteristics of the built environment than cyclists in unimodal cycling trips. The main focus of this research will therefore be on the contribution of the characteristics of buildings along the route to the train station to the willingness to cycle in access trips. In the literature review, building characteristics that potentially stimulate bicycle use are identified. To examine the contribution of these characteristics, a stated preference experiment with a rating task was executed. The results show that 'Distance to Buildings' contributes to the willingness to cycle to the largest extent relative to the other building characteristics when treating cyclists as a homogeneous group. This is followed by 'Building Height', 'Activity of the Ground Floor', 'Building Type', and 'Front Garden'. 'Openness of the Façade' contributes to the willingness to cycle to the smallest relative extent. Investigation of the heterogeneity in the data set showed that the evaluation of the characteristics is also influenced by gender, education, average cycling distance per week, and distance to the train station. Policy makers, architects and urban designers should use the results to create policies and designs that stimulate bicycle use. Urban planners should use the results to evaluate existing cycling routes to train stations.

Keywords:
Transportation mode choice | Bicycle | Access trips | Building characteristics | Rating experiment

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1. Introduction

1.1 Problem Definition

In 2018, motorized traffic caused 17% of the Greenhouse Gas (GHG) emission in the Netherlands. Private cars made up 62% of the total amount of GHG emission caused by motorized vehicles (Central Bureau of Statistics, 2019). With these high emission numbers, the car use should be reduced (Government of the Netherlands, 2019), however, the number of private cars in the Netherlands is still increasing. There was an increase in car ownership of approximately 11% in 2020 compared to the numbers of 2015 (Central Bureau of Statistics, 2020). This is not just happening in the Netherlands. In 2008, each second person in the European Union owned a car. Furthermore, between 80% and 90% of all passenger kilometers were made by car. The prediction was that these numbers would only increase in the coming years (Exel & Rietveld, 2009). This was found to be true several years later by Motieyan & Mesgari (2017). Private car use may be convenient, but research has shown that it comes with great societal costs such as traffic congestion, noise, and air pollution (Motieyan & Mesgari, 2017; Nordfjærn, Șimșekoglu & Rundmo, 2014). KiM Netherlands Institute for Transport Policy Analysis (2020) stated in their research that the more cars there are available, the less people use a sustainable transportation mode such as the bicycle. Additionally, Eldeeb, Mohamed & Páez (2021) found that households that own two or more cars are more likely to consider the car as their main transportation mode. There is a positive relationship between the number of private vehicles per household and driving a private vehicle. Reducing private car use, especially in urban areas, has been stated as a key sustainability aim (Redman, Friman, Gärling & Hartig, 2013).

The Dutch government aims at reducing the GHG emission levels by 95% in 2050 compared to the levels of 1990. In the National Climate Agreement, the government has stated the sectors where the reduction will have to take place. One of these sectors is 'traffic and transport' (Government of the Netherlands, 2019). As one of the action plans in this agreement the Dutch government aims at reducing car use by encouraging and investing in public transport. Looking at the percentages of car use and public transport use from 2019 in the Netherlands (Figure 1), it shows that the car – either used as a driver or passenger – is the transportation mode chosen for nearly 50% of all trips. Public transportation on the other hand (train, bus, tram and metro) was only chosen for 5% of all trips. This indicates that there is still a lot to gain when it comes to the use of more sustainable transportation modes.

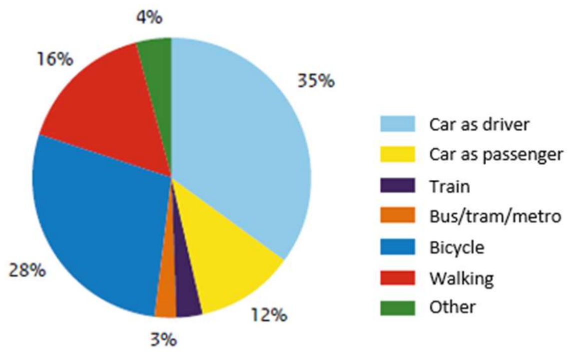

FIGURE 1 DIVISION OF TRANSPORTATION MODES BASED ON TOTAL AMOUNT OF TRIPS (KIM NETHERLANDS INSTITUTE FOR TRANSPORT POLICY ANALYSIS, 2020)

Various barriers have been identified for the use of public transport. Public transport journeys are for example often perceived as too long compared to journeys using the car. Although in practice this may not be the case, the transfers from one mode to another and the waiting time add to the perception that public transport journeys take too much time. Furthermore, public transport is often perceived as unreliable due to delays and overcrowded vehicles. Other barriers are the frequency, departure and arrival times, and locations of the public transport modes, which are not always in line with personal preference. People like to feel in control when travelling and the car offers them more control in terms of origin/destination, route and time planning (Beirão & Sarsfield Cabral, 2007).

One of the most underused modes of public transport is the train, while this transportation mode is one of the most sustainable transportation modes and at the same time can cover large distances (European Commission, 2021). A train station (predominantly in urban areas) can be considered a major public transport station. Major public transport stations commonly provide travel in multiple directions, have multiple transfer options, and a high frequency of the transportation mode (Ministry of Transport, Public Works and Water Management, 2010). The stations are located in areas with a high population and high employment densities and are therefore able to handle large quantities of people, both at the station itself and in the vehicles arriving at and departing from the station. A measure for encouraging train use proposed by the government is to increase the frequency of trains (Government of the Netherlands, n.d.-a). However, as there are more barriers for train use, this is not solely the solution for persuading people to travel by train. An important part of a train journey is the trip from home to the train station (access) and from the station to the destination (egress). There are travelers that avoid train travel due to low levels of accessibility of the train station (Givoni & Rietveld, 2007). By improving the accessibility to train stations, train travel could be increased. Furthermore, Givoni & Rietveld (2007) found that improved access to train stations will increase the overall level of satisfaction with train journeys as a whole (including the access and egress trip). When people's opinion of a train journey becomes more positive, they are more likely to change their transportation mode to the train.

There are various transportation modes that can be chosen for the access to or egress from a train station, e.g. walking, bicycle, car, and bus. Multiple studies suggest the use of the bicycle as an alternative transport mode to motorized vehicles for access and egress trips to train stations (e.g. Adnan, Altaf, Bellemans, Yasar & Shakshuki, 2019; Fan, Chen & Wen, 2019; Lee, Choi & Leem, 2016; Zuo, Wei, Chen & Zhang, 2020). In the Netherlands the bicycle is the most used transportation mode for access trips (Figure 2) (KiM Netherlands Institute for Transport Policy Analysis, 2016). To increase the accessibility of train stations, the Dutch national government is planning on implementing certain measures concerning the bicycle. These include among other things, an expansion of the bicycle parking facilities near train stations and increasing the bicycle connectivity using so-called cycling highways (Government of the Netherlands, 2019). Gehl (2010) furthermore states other advantages of increased bicycle use. When providing cyclists with two bicycle paths (one on either side of the road) of two meters wide, the capacity is 10,000 cyclists per hour. Comparatively, a two-lane, two-way street has a car capacity of 2,000 cars per hour at its peak. More people can be transported per hour when bicycle use is increased. Additionally, bicycles require less space in terms of parking. Approximately ten bicycles fit in the same space as one ordinary car parking place (Gehl, 2010).

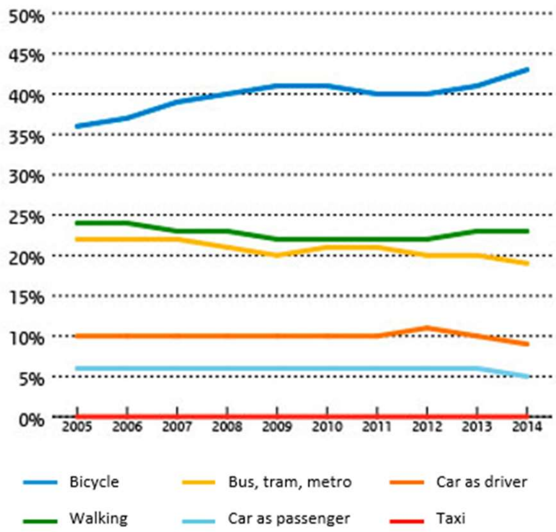

FIGURE 2 TRANSPORT MODES USED IN ACCESS TRIPS TO THE TRAIN STATION IN THE NETHERLANDS (KIM NETHERLANDS INSTITUTE FOR TRANSPORT POLICY ANALYSIS, 2016)

There is another factor that can improve the travel experience for access to the train station. Many studies have reported travel time as an important factor determining transportation mode choice (e.g. Akar & Clifton, 2009; Delclòs-Alió, Marquet & Miralles-Guasch, 2017; Olde Kalter & Groenendijk, 2018). The travel time can be divided into the objective travel time and the perceived travel time. The objective travel time can for example be reduced by encouraging the use of e-bicycles and creating so-called cycling highways (Ling, Cherry, MacArthur & Weinert, 2017; Olde Kalter & Groenendijk, 2018). The perceived travel time can be influenced by personal characteristics (e.g. gender and age) and trip characteristics (e.g. transportation mode and time of day) (Delclòs-Alió et al., 2017). Olde Kalter & Groenendijk (2018) found that the environment can influence the perceived travel time for cyclists. A pleasant cycling environment can shorten the perceived travel time, which can reduce the perceived travel time difference between the bicycle and the car. A pleasant cycling environment is characterized by the presence of greenery, cycling facilities, little traffic, and low building among other things (Olde Kalter & Groenendijk, 2018). This perceived time reduction can persuade people to choose the bicycle (in combination with the train) over the car as the transportation mode.

The environment is a broad subject to study in combination with cycling. Various studies have looked into aspects such as infrastructure, traffic intensity, or the effect of greenery alongside a cycling route (e.g. Grudgings, Hughes & Hagen-Zanker, 2021; Van der Waerden, Willems & Van Dongen, 2018; Winters, Brauer, Setton & Teschke, 2010). However, what seems to be missing in the literature, despite the fact that much of the environment – and more specifically, the routes to train stations – is made up of buildings, is the role of buildings and their characteristics in the perception and appeal of cycling routes which, if reviewed positively, can stimulate bicycle use. In current times, buildings are often designed individually, repeatedly without considering the connecting streets, greenery, and most importantly other buildings in the vicinity. There is an urge to create impressive buildings that can be seen from a distance (Bond, 2017; Gehl, 2010). However, due to this mentality the human scale of buildings has become lost. The lack of human scale makes walking and cycling less appealing, and contributes to a car-oriented society (Gehl, 2010). This indicates that there might be building characteristics that are related to the transportation mode choice. Liu (2021) researched cyclists' preferences for characteristics of the built environment in access trips to metro stations. Liu (2021) stated that cyclists who travel to metro stations appear to have different preferences for characteristics of the built environment than cyclists who are engaged in unimodal cycling trips. This leaves a knowledge gap for the effect of building characteristics on the willingness to cycle for access trips to the train station. When there is a better understanding of the preferences of cyclists regarding appearances of buildings on the route to the train station, areas can be (re)developed to comply with these preferences. In addition, more attention for building designs suitable for cyclists can help encourage bicycle use to access train stations and will make the access trip to the train station more pleasant, which will reduce perceived travel times and improve the overall satisfaction level for train journeys. This in turn will persuade more people to choose sustainable transportation modes (the bicycle and the train) over the car, contributing to the reduction of GHG emission, traffic congestion, and the demand for car parking.

1.2 Research Question and Objective

Research has been conducted regarding the choice for the bicycle as a mode of transport and the factors that contribute to this choice in general, but limited attention has been paid to the use of bicycles for access and egress trips. There are some studies that investigated bicycle use in these trips. Sanders (2015) paid attention to preferences based on variables such as traveling time, cost, and safety regarding the choice for the train or the car as the main transportation mode, with the bicycle being one of the options for the access trip. Malaquias Bandeira (2018) focused on the egress trip, researching what the influence is of urban bicycle sharing systems on the transportation mode choice. However, these studies focus on practical variables and do not take into account the influence of the built environment, while this also plays a role in the transportation mode choice. Liu (2021) has looked into the influence of environmental characteristics on bicycle use in access trips. However, only building height was included in terms of building characteristics and no studies could be found that investigate other building characteristics in relation to cycling, still leaving a knowledge gap for the contribution of other building characteristics on the willingness to cycle. The main focus of this research will therefore be on the contribution of the characteristics of buildings along the route to the train station on the willingness to cycle in access trips. The aesthetics of buildings (e.g. historical property) as well as the purpose (e.g. restaurant) or characteristics of the buildings related to its direct surroundings (e.g. distance of a building to the road) can play a role in the choice of using the bicycle in access and egress trips. The aim of this graduation research will therefore be to examine if and to what extent buildings characteristics can stimulate bicycle use in access trips. This translates to the main research question:

"To what extent do building characteristics along the route stimulate people to use the bicycle as an access mode to major public transport stations?"

In order to answer the main research question, the following sub-questions are defined:

1. What are access trips in train journeys?
2. Which characteristics influence transportation mode choice and particularly the choice for the bicycle (in general and for access trips in train journeys)?
3. Which building characteristics have the potential to stimulate bicycle use (in general and for access trips in train journeys)?
4. How do people evaluate the building characteristics in relation to the decision to cycle to train stations and can differences between groups of people be identified?
5. Is there a difference in the evaluation of building characteristics for cycling in general and cycling to the train station?
6. Is there a relation between building characteristics and the evaluation of the attractiveness and bicycle-suitability of an environment?

The objective of this research is to gain more insight into the role buildings along the route to the train station play in the willingness to cycle for access trips by investigating the contribution of building characteristics to this willingness to cycle. The way this is done, is by measuring the preferences of cyclists for various building characteristics on the route from home to the train station. The results of this research will be presented as advice for policy makers, architects and urban designers that can assist them in creating policies and designs that stimulate bicycle use to train stations.

1.3 Research Approach

To keep the scope of this research manageable, the choice was made to only focus on bicycle trips to the train station, as there are considerable differences between the train and other public transportation modes, for example in the travel distance and level of comfort. Furthermore, only access trips to the train station are included, due to differences between access and egress trips, with a major difference in the availability of transportation modes. Even though there are multiple sustainable transportation modes that can be chosen for an access trip to a train station, this research will focus on the bicycle. The environment has been identified as an influential factor in the decision to cycle. However, the environment is a broad topic to investigate, so in order to narrow the scope the choice is made to only research building characteristics, as this is a missing element in the existing literature.

The research will start with a literature review to answer the first three research questions (Figure 3). The review consists of three parts. The first two parts serve to acquire the necessary background information on access trips, and transportation mode choice, with particular attention for the choice for the bicycle. This will create the context in which this research takes place. The third part of the literature review will investigate building characteristics that have the potential to stimulate bicycle use. For this it is important to understand people's perception of buildings in general and specifically while travelling. This will help in the decision which characteristics to include in the next part of the research.

After the literature review, the methodology will be explained. A stated preference experiment with a rating task will be used to investigate the contribution of certain building characteristics to the decision to use the bicycle as an access mode to the train station. Subsequently, statistical analysis will be performed on the collected preference data to determine which of the included building characteristics can stimulate bicycle use for access trips to a train station. The analysis will be extended by investigating if differences in groups of people can be identified and if certain personal characteristics can be linked to the identified groups. The statistical analysis serves to answer the last three research questions.

After the analysis of the data, conclusions can be drawn based on the results and the main research questions can be answered. The final outcome of the research will be advice for policy makers, architects and urban designers that can be used to create policies and designs that stimulate bicycle use (for routes to train stations).

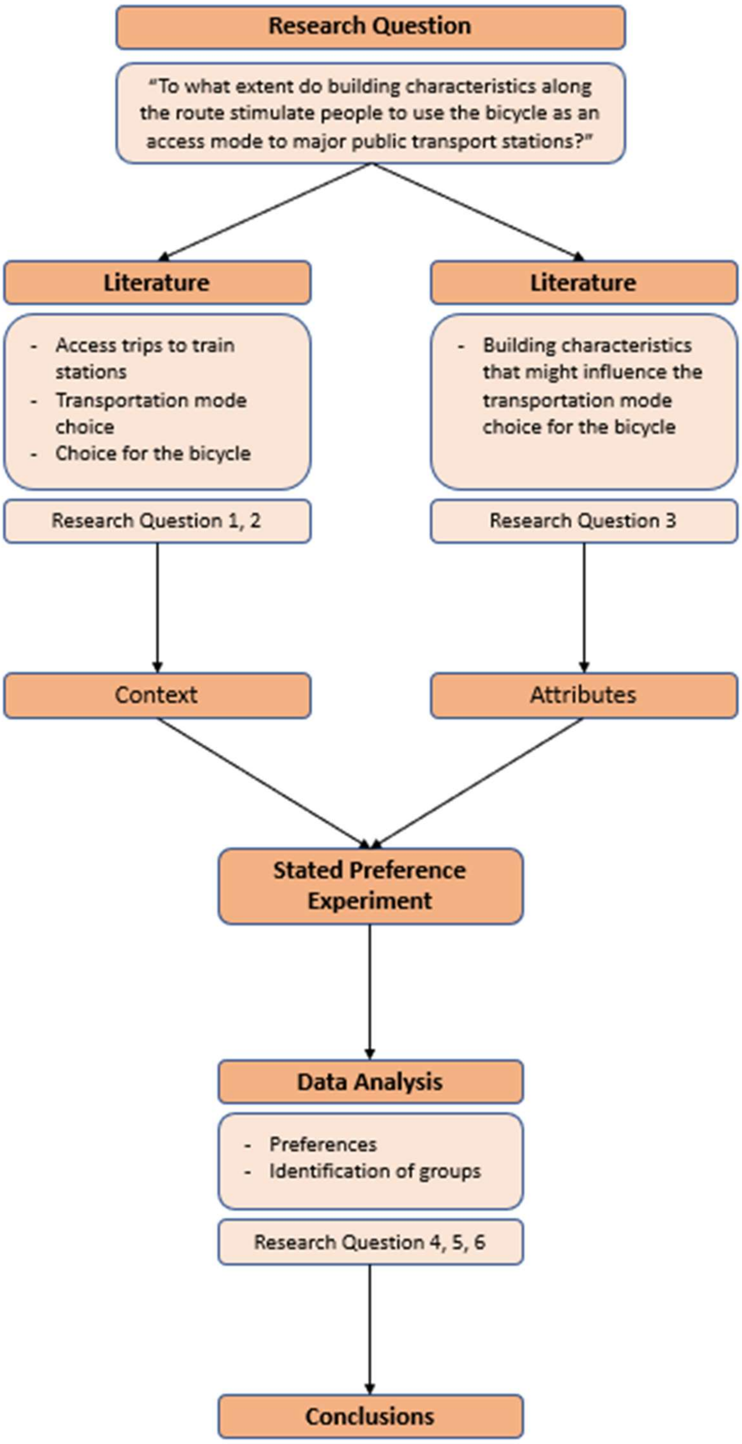

FIGURE 3 RESEARCH APPROACH

1.4 Relevance of the Research

As mentioned in paragraph 1.1, car use keeps increasing, which causes several issues such as an excess of GHG emission, traffic congestion, and a high demand for car parking. To contribute to the reduction of the GHG emission car use has to be lowered. Over the past years, the human-scale in buildings has become lost due to the need to create impressive individual buildings. The loss of human-scale makes the environment less appealing for cycling, and people are more likely to use the car (Gehl, 2010). More knowledge about the role of buildings in for example the decision to cycle can provide urban planners insight in the success of existing access routes towards train stations for cyclists. Additionally, the gained knowledge can assist architects and urban designers in creating designs that stimulate bicycle use, and consequently make the access part of a train journey more appealing. With the improved access part of the train journey it is expected that more people will choose the train over the car as their transportation mode. First of all, this will benefit the public transport companies as the number of travelers will increase. This switch will also benefit the travelers, as they reduce their own environmental footprint, and improve their personal health due to more physical exercise caused by the cycling. Furthermore, they will no longer have to deal with traffic congestion and car parking problems. In addition, increased train use in combination with cycling will help the government reach the GHG emission reduction goal and will require less investments in infrastructure for the car.

1.5 Reading Guide

This chapter provided a brief introduction of the research. In the following chapters, the remainder of the study is reported. Chapter 2 discusses the literature review that will place this research in context and will provide the building characteristics that are to be researched in the preference experiment. In chapter 3, the methodology of the research is explained. This chapter includes the underlying theoretic methods for the preference experiment and the data analysis, as well as the setup of the preference experiment, the communication method of the attributes, and describes the distribution of the experiment. The results from the analyses are reported in chapter 4, starting with the descriptive statistics of the sample, followed by the statistical analyses of the collected preference data. Chapter 5 presents the conclusions and discussion of the research along with recommendations for policy and practice. In this chapter, the main research question is answered.

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2. Literature Review

This chapter contains the literature review that was conducted to gather detailed information regarding the topic of this thesis. The review can be divided in three parts: access and egress trips, transportation mode choice, and building characteristics. Paragraph 2.1 discusses access and egress trips with the aim to define what access trips in relation to train journeys are and to create an understanding of the importance of access trips in relation to the use of sustainable transportation modes. Paragraph 2.2 focuses on transportation mode choice. This paragraph gives more insight into the possible factors that influence the choice for the bicycle. Because this research concerns the use of the bicycle in access trips, this paragraph mainly takes into account the choice for the bicycle, and, where necessary, will elaborate on transportation mode choice factors for other transportation modes. Paragraph 2.3 is about building characteristics. First, the perception of buildings is discussed to get a general idea of how buildings are seen in general and while traveling. Next, building characteristics that were found in the literature review that could stimulate bicycle use in access trips are described. Finally, in paragraph 2.4 the conclusions of the literature review are presented and the building characteristics that seem most promising for the continuation of the research are presented.

2.1 Access and Egress Trips

When someone is about to undertake a journey, a decision has to be made regarding the transportation mode that they are going to use. In general first the main mode is selected, commonly a choice between the car and public transport, which in this research is limited to the train. A car journey can be considered as a unimodal journey. A unimodal journey is a journey for which only one transportation mode is used to travel from origin to the destination of the journey (KiM Netherlands Institute for Transport Policy Analysis, 2014). The traveler gets in the car close to or at the origin, drives almost the full travel distance to a parking place as close to the destination as possible, and finishes the journey by walking the small distance from the parking place to the destination. However, a traveler may also opt to travel by train. A train journey can be considered a multimodal journey (Figure 4). This is a journey that involves the use of two or more different transportation modes to travel from origin to destination and commonly transportation mode transfers are required. When undertaking a journey by train there is usually more to it than solely the train trip. The train trip is part of a chain of trips that also considers the journey to and from the train station using different transportation modes (Givoni & Rietveld, 2007). There are at a minimum three trips to the journey: going from the origin to the train station (the beginning), the train trip (the middle), and going from the train station to the destination (the end). The beginning and the end of an individual's public transport journey is respectively called the access and egress trip – often also referred to in literature as the 'first- and last-mile' (Thomson, 2020).

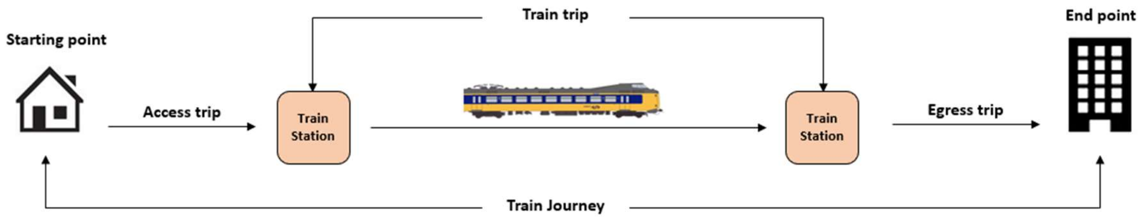

FIGURE 4 MULTIMODAL TRAIN JOURNEY, ADAPTED FROM (SANDERS, 2015)

The distance between the origin and the train station or the train station and the destination can be larger than travelers are willing to walk or cycle, creating a gap between location and destination that often requires travelers to choose another transportation mode for the access and egress trip or even causes travelers to choose an alternative direct transportation mode due to increased effort (Mo, Shen & Zhao, 2018). According to Bouton et al. (2017) there is a drop of 90% in the use of public transport if the walking distance for the access or egress trip is more than half a mile (approximately 800 meters). This means that if the distance is greater than half a mile people tend to use motorized vehicles to reach the train station or their destination or refrain from using public transport at all. The KiM Netherlands Institute for Transport Policy Analysis (2020) found that in the Netherlands the bicycle is more often chosen as a transportation mode in access trips (Figure 5). People are on average willing to cycle 2.6 kilometers to the train station. This means that if the distance becomes fairly larger than 2.6 kilometers people tend to switch to motorized vehicles. The limited willingness to walk or cycle is a problem when the aim is to encourage the use of sustainable transportation modes. Part of this problem is that people tend to choose the transportation mode option that is most beneficial considering time, money, and effort.

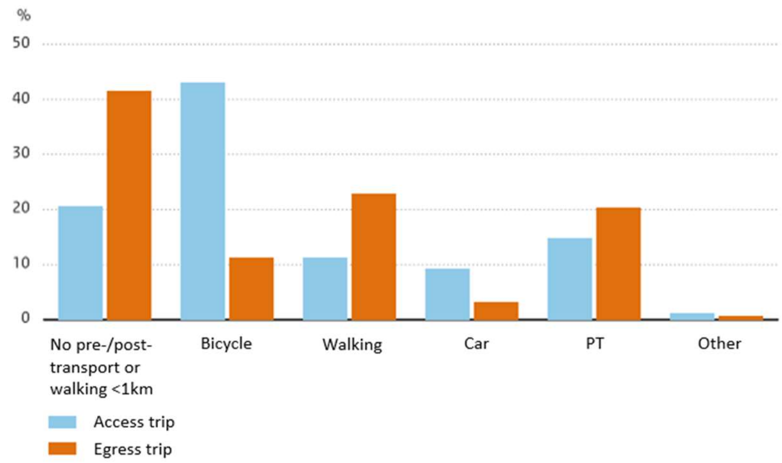

FIGURE 5 TRANSPORTATION MODE USED IN ACCESS AND EGRESS TRIPS (KIM NETHERLANDS INSTITUTE FOR TRANSPORT POLICY ANALYSIS, 2020)

Choosing a transportation mode can consist of two levels. The first level is the choice for the main transportation mode. The second level occurs when public transport is chosen, because then the choice will have to be made how to reach the train station, or in other words, what type of pre-transport will be used in the access trip. If a journey by train in combination with other transport modes for the access and egress trip will result in high costs, long waiting times, and multiple transfers, people are more likely to use the car. People will switch their transport mode if the overall experience is fast and convenient. This means that if the access and egress transportation mode options in combination with public transport provide an experience that is as good as or better than the car, more environmentally friendly transport modes will be chosen. It is therefore important to reduce the total journey time and effort for the combination of the train and access and egress transportation mode options (European Environment Agency, 2019). According to Givoni & Rietveld (2007) integration of the journey components (the trips) is crucial to achieve continuous travel, which entails short waiting times and little effort, and make the train an attractive alternative to the car.

Important in the transportation mode choice for public transport is accessibility. The access and egress part of a train journey are determining factors for the accessibility of a train station. The access to the station is partly defined by the distance people are willing to walk or cycle (Zuo et al., 2020), but also in the more literal sense by e.g. the number of roads leading to a station. The European Environment Agency (2019) found that the walking environment influences the perceived walking distance and time. Their report showed that a catchment area for a bus stop became three times larger when the environment was 'human-scaled' instead of more car-oriented. They argue that similar effects may also occur for other transport modes, saying that for example nicer cycling routes can attract more cyclists and reduce perceived travel times and distances. This is in line with the findings of Mo et al. (2018), who state that built environment variables can influence travel behavior in access and egress trips. Additionally, accessibility can be related to the availability of transportation modes to reach a train station. This is where an important difference is between the access and egress trip. Generally, for the access trip people have multiple transportation modes available, including privately owned modes such as a car or a bicycle. For the egress trip people are usually dependent on the available transportation modes in the proximity of the station. A problem with this is that there is often limited availability of different transportation modes. This availability is further restricted by possible high costs of the transportation modes (Keijer & Rietveld, 2000). Givoni & Rietveld (2007) have researched the effects of the access trip to a train station on the perception of the overall train journey. Their results indicate that high quality access trips can contribute to more satisfaction and a better perception of train journeys as a whole (i.e. the full journey, including the access and egress trip), and that there is still significant scope for improving the accessibility of train stations. They also concluded that by improving the accessibility of train stations, and therefore by improving the access trip, people who seldom or never travel by train can be persuaded to travel by train more often.

2.2 Transportation Mode Choice

When traveling, an important choice that has to be made is what transportation mode(s) will be used to reach a destination. Various studies have been conducted in determining what drives the transportation mode choice. A model that summarizes the results of many of these studies is proposed by Schneider (2013) (Figure 6). According to Schneider (2013) there are five steps in the mode choice decision process. The first step is 'Awareness & Availability', which entails the transportation modes that are available to the traveler in the choice process. Next are the second, third and fourth steps and these consist of situational tradeoffs. Schneider states that these steps can be considered simultaneously or in various sequences and therefore do not necessarily follow the order proposed in the model. 'Basic Safety & Security' includes the perception of safety from traffic collisions and the security from crime. 'Convenience & Cost' includes all the considerations concerning time, money, and effort. 'Enjoyment' is focused on choosing a transportation mode that provides the most personal benefits. The first four steps are all influenced by socioeconomic factors. The last step is 'Habit', which simply means that people tend to use the transportation mode that they regularly use or have previously used for the same trip purpose. In the next sections the steps as well as the influence of the socioeconomic factors will be further explained.

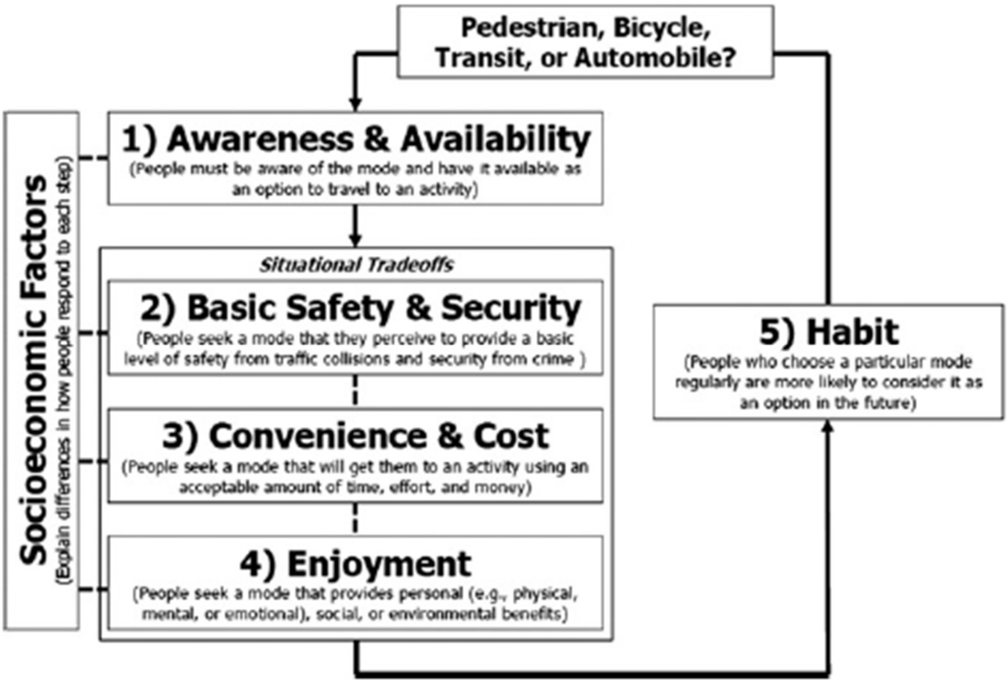

FIGURE 6 THEORY OF TRANSPORTATION MODE DECISIONS (SCHNEIDER, 2013)

Awareness and Availability

According to Schneider (2013) people must be aware of a transportation mode and must have it available as an option to consider using that transportation mode for their journey. For example, when a person lives in a car-oriented neighborhood the choice for the bicycle is not very likely to be considered as the presence of bicycles in their environment, and with that the awareness of the option 'bicycle' as a transportation mode, is very low. Same goes for availability of certain transportation modes. When a person does not own a driver's license the choice to drive a car will not be considered as a possible transportation mode choice.

In the decision between various transportation modes, people choose from a set of alternatives that is applicable to them and their situation. This set of alternatives is referred to as the 'choice-set', and a distinction can be made between objective and subjective choice-sets (Van Exel & Rietveld, 2009). The transportation mode alternatives in an objective choice-set are determined by the availability of transportation modes, in which the accessibility to transportation networks – e.g. whether or not the appropriate infrastructure is present for a transportation mode, or if public transport is provided in the area – is included (De Witte, Macharis, Lannoy, Polain, Steenberghen & Van de Walle, 2006; Van Exel & Rietveld, 2009), and the capabilities of the traveler – e.g. when a person has a physical disability the option to walk or cycle is often excluded from the choice-set (Van Exel & Rietveld, 2009). The alternatives in a subjective choice-set are based on the transportation mode options the traveler is aware of and considers to be feasible and acceptable for their journey. This subjective choice-set is a sub-set of the objective choice-set and is the set that is actively considered in the transportation mode decision (Van Exel & Rietveld, 2009).

Awareness of certain transportation modes can be increased by improving the image people have of that transportation mode. For example, Beirão & Sarsfield Cabral (2007) found that a barrier for the use of public transport is that especially car users often have a negative and inaccurate perception of public transport and consequently will not switch their transportation mode, while in practice public transport is better than the idea car users have of it. By actively working on improving the image of public transport, part of the car users will add public transport to their subjective choice-set and will (at least occasionally) switch to public transport. In the Netherlands, awareness for the bicycle is raised at a young age. Children are educated about and trained in safe and effective cycling techniques and traffic rules in school (Pucher & Buehler, 2008). This removes the barrier attached to cycling concerning safety perception and makes children aware of the bicycle as a transportation mode option which will continue into adulthood.

In terms of availability, the Netherlands is working hard to increase the availability of (public) transport modes. The frequency of trains is increased to accommodate more people (Government of the Netherlands, n.d.-a) and various measures have been and will further be taken in the future to make public transport accessible for all people. For example, trains have their entrance aligned with the platform for easier boarding, and there is more assistance available for people with a disability. Additionally, buses have special seating for people in a wheelchair as well as elderly travelers, disabled people, and pregnant women (Government of the Netherlands, n.d.-b). There is also a special arrangement for students, making it possible for them to travel for free using public transport using a student-PT (OV) card (Dienst Uitvoering Onderwijs, n.d.).

Furthermore, the Netherlands has an extensive bicycle network, which makes cycling a feasible transportation option for the majority of the Dutch population. The Dutch national government creates design guidelines for the bicycle network and offers funding (Pucher & Buehler, 2008). Similarly, there are sidewalks available alongside many Dutch roads. Although in theory walking is an available transportation mode for many people in many situations, the presence of sidewalks will increase walking trips (Eldeeb et al., 2021). All the measures taken are aimed at increasing the availability of transportation modes for as many people as possible.

Basic Safety and Security

Schneider (2013) states that people seek to travel using a transportation mode that provides them with a basic level of safety from traffic collisions and security from crime. Safety is divided in two topics that are closely related: traffic and infrastructure. Security is focused on crime in relation to the transportation mode choice.

<u>Traffic</u>

Based on a study by Parkin, Ryley & Jones (2007), traffic factors that influence the perception of risk for cyclists include the traffic volume, speed, the composition of motor traffic, and the number of parked vehicles along a cycling route. The traffic volume and speed are often considered the most important traffic aspects to impact the transportation mode choice for the bicycle. Grudgings et al. (2021) examined the influence of these aspects more in-depth on the willingness to cycle. As opposed to Parkin et al. (2007), Grudgings et al. (2021) concluded that traffic volume has a lesser influence on the willingness to cycle. However, they did find that above-average vehicle speeds (average: 29.3 km/h) alongside a cyclist's route affect the decision to cycle negatively. When the traffic speed along the majority of a cyclist's route is under approximately 30 km/h, the probability that a person chooses to cycle will increase. Grudgings et al. (2021) therefore state that speed limits up to 30 km/h might encourage cycling. Lastly, they claim that the combination of high speeds and large volumes of traffic does impact the decision to cycle, as roads that have both can act as barriers for cyclists.

Pucher & Buehler (2008) consider the Netherlands as an example for traffic calming measures. In line with the advice from Grudgings et al. (2021), most streets in residential neighborhoods in the Netherlands have a speed limit of 30 km/h and areas that have been assigned the label ‘woonerf (home zone)’ even require cars to drive at walking speed. This enables a safe start for a cycling journey from home. Furthermore, in many city centers there are car-free zones to accommodate pedestrians and cyclists. Additionally, many infrastructural traffic calming measures are present in Dutch streets, such as raised intersections, roundabouts, and road narrowing to slow motorized traffic down and increase safety for pedestrians and cyclists. Finally, Pucher & Buehler (2008) believe that there is also safety in numbers. The large number of cyclists in the Netherlands makes other road users more aware of the presence of cyclists.

Infrastructure

Pucher & Buehler (2008) reviewed the success factors for cycling in the Netherlands, Germany, and Denmark. They found that, regarding infrastructure, bicycle paths that are separated from roads are preferred by cyclists. Additionally, Grudgings et al. (2021) state that a greater proportion of separate bicycle paths is likely to increase bicycle use. Separate bicycle paths alone are not sufficient infrastructure for cyclists but already make cycling a viable transportation option for many people (Akar & Clifton, 2009; Pucher & Buehler, 2008). Schneider (2013) added that in combination with the separated bicycle paths, lower volume streets also reduce the amount of cars, which improves safety for cyclists. Furthermore, Pucher & Buehler (2008) observed that the bicycle networks in the Netherlands, Germany, and Denmark all include many off-street short-cut connections for cyclists between streets and city blocks, making more direct trips possible almost entirely on separate bicycle paths. In addition, they identified bicycle streets as a bicycle-increasing infrastructure measure, where cars are allowed but cyclists have priority over the entire width of the street. Lastly, Pucher & Buehler (2008) noticed the success of the large number of bicycle parking facilities present, which allows for easy parking when traveling by bicycle. Overall, they concluded that these infrastructure facilities for the bicycle make cyclists feel safer in traffic and experience less stressful cycling trips.

Crime

Crime was found to be only relevant for pedestrians and cyclists. Gatersleben & Uzzell (2007) concluded that car users and public transport users worry less about safety. Schneider (2013) identified concerns about personal safety to be a barrier for walking and cycling. His study showed that the interviewees felt less safe walking because that was how they became victims of crime in previous situations or they feel like they are a target when walking alone.

The safety from crime related to the bicycle mainly concerns bike theft. Many potential cyclists are concerned their bicycle will get stolen (Schneider, 2013). Even in the Netherlands, where cycling is a common mode of transportation, bike theft is still a major problem. However, current policy focuses on increasing the security of bicycle parking (Pucher & Buehler, 2008).

Convenience and Cost

People tend to choose the transportation mode option that will cost them the least time and money and requires the least amount of effort on their part. The amount of personal control over travel movements is also included in the convenience of a transportation mode

(Schneider, 2013). Three of the most important aspects of 'Convenience and Cost' will be explained: travel time, monetary costs, and physical and cognitive effort.

Travel time

One of the most researched topics in relation to transportation mode choice is the effect of travel time. Many studies have concluded that travel time is one of the key factors in transportation mode choice (e.g. Akar & Clifton, 2009; Beirão & Sarsfield Cabral, 2007; Delclòs-Alió et al., 2017). Akar & Clifton (2009) stated, based on their research, that people will choose the transportation mode with the shortest travel time, all else being equal. Delclòs-Alió et al. (2017) make an important distinction in travel time between objective and perceived travel time. The objective time is the factual journey time, whereas the perceived time is the amount of time the travelers feel they have been traveling. Delclòs-Alió et al. (2017) concluded from their research that the travel time for non-motorized transportation modes is more likely to be over-perceived, as opposed to the travel time for motorized vehicles which is generally under-perceived. They also found that for trips with an objective travel time under 30 minutes the perceived time is often over-perceived in contrast to trips over 30 minutes. Additionally, Olde Kalter & Groenendijk (2018) state that the area of a trip also influences the perceived travel time. The travel time for trips conducted in urban areas is often over-perceived and the travel time in sub-urban and rural areas under-perceived. Beirão & Sarsfield Cabral (2007) have examined the influence of travel time on the choice between the car and public transport. They derived that the travel time by car is perceived as less than the time by public transport. They attribute this result to car drivers feeling more in control of their journey and feeling that they can avoid traffic by taking alternative routes. Delclòs-Alió et al. (2017) furthermore state that the transfers between transport modes can also negatively influence the perceived travel time for public transport. Van Exel & Rietveld (2009) have also concluded that the perceived travel time for public transport is higher than the objective travel time. They further claim that a more accurate perceived travel time for public transport will increase the probability of people considering public transport as a transportation mode option.

According to Akar & Clifton (2009), people are more sensitive to time for non-motorized transportation modes. Travel time has been identified as a prominent barrier for walking and cycling (Schneider, 2013). Specifically focusing on the bicycle, Akar & Clifton (2009) argue that by decreasing the time spent cycling the mode share of the bicycle will increase. The measures they propose for decreasing cycling time are implementing road facilities for cyclists (e.g. bike lanes) and arranging the waiting times at intersections to favor non-motorized transportation modes. Ling et al. (2017) and Olde Kalter & Groenendijk (2018) furthermore add that the use of an electric bicycle as opposed to a normal bicycle and the creation of so-called cycling highways contribute to the reduction of cycling time. Thus, these measures will decrease the objective cycling time. Gatersleben & Uzzell (2007) and Olde Kalter & Groenendijk (2018) state that the perceived cycling time is among other things influenced by the environment. Boring journeys – i.e. journeys where there are too little stimuli – are perceived as longer time-wise. Olde Kalter & Groenendijk (2018) found a relationship between the attractiveness of a route and the perceived travel time for cyclists. An attractive cycling route will make the travel time appear shorter.

A factor related to travel time that is often mentioned as a barrier for the use of public transport is the reliability of the transport mode. Especially car users perceive public transport to be unreliable in terms of time schedules and delays. This perception is based on previous experiences using public transport and word-of-mouth from other people's experiences.

Especially for the bus, people experience a lack of control of their journey and personal time schedules due to uncertainty when their transport will arrive. When people travel by car they feel more in control and able to keep to their personal timetables (Beirão & Sarsfield Cabral, 2007). Furthermore, Beirão & Sarsfield Cabral (2007) found that between public transport modes the train is preferred over the bus as people appear to perceive the train as more reliable.

Monetary Costs

Among others, Akar & Clifton (2009) concluded that mode choice is sensitive to monetary costs. People will choose the transportation mode that is the cheapest. The outcome of Akar & Clifton's (2009) research however has been refuted by Beirão & Sarsfield Cabral (2007). Beirão & Sarsfield Cabral (2007) researched the transportation mode choice for the car versus public transport and found that despite public transport being the cheaper option in their research area (Porto, Portugal), monetary costs were not considered a key factor for changing to public transport. Nonetheless, there are multiple studies that underline that costs do have a significant influence on the transportation mode choice, even if it is not the biggest contributor. For example, Schneider (2013) and Van Exel & Rietveld (2009) determined that higher costs do discourage car use. A quick measure to increase driving costs is the increase of parking costs (Akar & Clifton, 2009). Schneider (2013) found that in areas with expensive parking car use was discouraged. In addition, Van Exel & Rietveld (2009) concluded that the increase in parking costs would lead to an increase in public transport use. Van Exel & Rietveld (2009) furthermore found a relationship between the transportation mode choice and the question who pays for transport in commute trips. Their results indicate that when travelers have to pay for a trip themselves they will consider more transportation mode options. When their employer pays for a trip with a specific transportation mode, the probability increases that the traveler will choose the compensated transportation mode. The employer could therefore have an important role in the stimulation of more sustainable transportation modes. Research by Ton, Duives, Cats, Hoogendoorn-Lansar & Hoogendoorn (2019) shows that the effect of compensation for a specific transportation mode is highest for public transport and lowest for the bicycle. The low influence of monetary costs on the choice for the bicycle is confirmed by Majumdar & Mitra (2013), who found economic factors to have the least influence on the choice for the bicycle of all the user-related factors in their research.

Physical and Cognitive Effort

Various studies have concluded that an increase in physical and cognitive effort will diminish the chance of a certain transportation mode being chosen. The car is the favored transportation mode when the distance to facilities is large and car parking is plentiful at the destination. In this situation traveling by car results in the least amount of effort and is therefore considered to be the most convenient. The opposite was found for situations where facilities are nearby. Areas with mixed land-use create short trips between home and different types of facilities (e.g. the office, shops, and schools). In these areas parking was often more limited. The combination of short trips and limited parking for cars works in favor of public transport, walking, and cycling. The effort for using the car is increased, while the barriers for the other transportation modes are reduced (Ma & Cao, 2019; Pucher & Buehler, 2008; Schneider, 2013). A barrier based on cognitive effort can be identified for public transport. Occasional public transport users and car users indicated that they often do not have enough information regarding the journey by public transport, especially concerning routes and timetables. This leads to the perception that public transport is difficult to use (Beirão & Sarsfield Cabral, 2007). Furthermore, public transport was found to be tiresome because it generally requires several changes between transportation modes (Gatersleben & Uzzell, 2007). However, if the transfer and overall journey are perceived as easy and fast, people are less affected by transfers and are more likely to switch transportation modes (Beirão & Sarsfield Cabral, 2007; European Environmental Agency, 2019). From this it can be derived that increasing information about public transport journeys and easing transfers between public transport modes have the potential to persuade travelers to switch to public transport. In the Netherlands the importance of cycling for the use of public transport (particularly the train) has been recognized by the government and transport companies. Cycling is integrated with train travel by providing bicycle parking at stations in city centers and at more rurally located stations along the rail network. It is furthermore possible for cyclists to take their bicycle with them on the train for an additional fee (Pucher & Buehler, 2008). This eases the transfer between bicycle and train, making the public transport journey more attractive. For cycling in general, Majumdar & Mitra (2013) state that topography is a barrier. Uneven and hilly roads make cycling more difficult and consequently require more physical effort (Parkin et al., 2007; Winters et al., 2010). Attention should be paid to landscape and route design to make cycling appealing.

Enjoyment

Schneider (2013) states that people seek to travel using a transportation mode that provides them with personal physical, mental, or emotional benefits. This is captured in the term 'Enjoyment'. Enjoyment can indicate liking the transportation mode activity itself (e.g. people like to drive, or people enjoy cycling), but it also entails other aspects. Three aspects that can be categorized under 'Enjoyment' will be discussed: comfort, the environment, and weather.

<u>Comfort</u>

According to Heinen, Maat & Van Wee (2011), people base their transportation mode choice on the direct personal benefits related to time, flexibility, and comfort. Olde Kalter & Groenendijk (2018) even state that comfort aspects might have a larger influence on the transportation mode choice than travel time. Comfort is a topic that is closely related to other topics such as safety, convenience.

While many people enjoy driving a car, there is also a large group of people who experience stress while driving, particularly when they are dealing with traffic congestion or complex traffic situations. These people are more prone to use public transport. A beneficial factor of public transport is that it offers people the opportunity to relax and for example read a book because they are not driving themselves. The level of comfort that is associated with public transport further depends on the temperature in the vehicle, which has to be pleasant, and the availability of a seat (Beirão & Sarsfield Cabral, 2007). Additionally, the service quality of public transport is important, which entails the reliability of the transportation mode, the travel speed, and the frequency (De Witte et al., 2006).

People who use active transportation modes feel more comfortable and less stressed on routes that are free of traffic (Parkin et al., 2007). As previously mentioned in the section 'Basic Safety and Security', there are various traffic calming measures that can reduce the volume and speed of motorized traffic, creating a more comfortable environment for cyclists and pedestrians. For cyclists in particular, there are aspects that can contribute to or reduce the level of comfort. For example, when cyclists have to put in much effort, their level of comfort goes down and the mode share for cycling will decrease. High effort can be caused by cyclists needing to make frequent stops along a route (e.g. due to traffic lights), coming across sharp corners, and poor topography (e.g. many slopes). The level of comfort of cyclists can be increased by providing well-maintained bicycle paths that are separated from the main road (Olde Kalter & Groenendijk, 2018; Parkin et al., 2007; Winters et al., 2010).

Gatersleben & Uzzell (2007) further mention that besides traffic danger aspects, there are other inconveniences that can cause an uncomfortable travel experience. Two of the most mentioned aspects that make people uncomfortable are noise during their journey and travel delays (Gatersleben & Uzzell, 2007; Winters et al., 2010). Greenery is an aspect that can create a calming and comfortable environment to travel in, though this has to be regulated to avoid feelings of unsafety (Bond, 2017; Van Belois, 2016). The topic of greenery will be further discussed in the section 'Environment'.

Environment

Winters, Davidson, Kao & Teschke (2011) determined that pleasant route conditions are among the strongest motivators for bicycle use. Olde Kalter & Groenendijk (2018) concluded that the attractiveness of a cycling route is greatly influenced by the aesthetics along the route and even found that attractiveness has the highest influence on route choice for routes of similar distances. Olde Kalter & Groenendijk (2018) state that the environment characteristics that have a positive effect on the attractiveness of the environment and the cycle experience are characteristics that contribute to a feeling of calm and tranquility. However, too little stimuli, and consequently too much tranquility, can make an environment and the cycle experience seem boring.

Bond (2017) states that the visual complexity of natural environments can act as a kind of mental balm. Therefore, one of the factors that can contribute to the feeling of tranquility is greenery. Van Dongen & Timmermans (2019) found that the more greenery is present, the more positive the evaluation of the environment. Furthermore, they examined the influence of various types of greenery and concluded that hedges and flowers are preferred over grass. Nevertheless, grass is often used to add greenery to an environment as it is easy to place and to maintain. Considering trees, Van Dongen & Timmermans (2019) concluded that large trees are the preferred type. Van der Waerden et al. (2018) researched the optimal height of trees for an attractive environment and found that trees with a height between 8 and 15 meters are considered the most attractive. The explanation Van Dongen & Timmermans (2019) propose for the preference of large trees, hedges, and flowers over grass is that the visual impact of these types of greenery is larger than for grass. It should be mentioned that greenery can also have a negative impact on the evaluation of the environment. Van Belois (2016) found that when trees and bushes are too close to the bicycle path they can make people feel unsafe. Especially women appear to feel more stressed when cycling in an environment with trees and bushes close to the bicycle path. Van der Waerden et al. (2018) state that the minimal distance trees should be placed from the bicycle path is one meter.

Another aspect of the environment that has been extensively studied is the infrastructure. This has been previously discussed in the section 'Basic Safety and Security'.

Weather

According to Parkin et al. (2007), the experience of a cyclist is partly determined by the environment through which they cycle. In turn, this environment is to some extent influenced by climatic conditions. Thomas, Jaarsma & Tutert (2008) have researched the influence of various weather-related factors on cycling and found that temperature is regarded as the most important. This is followed by the amount of sunshine, the duration of precipitation, and the wind speed. A low temperature, precipitation (rain and snow), and high wind speeds have a negative effect on cycling (Helbich, Böcker & Dijst, 2014). Helbich et al. (2014) found that temperature has a lesser influence on cycling in central urban areas compared to more open and rural areas. Densely built environments provide warmer microclimates when the general outside temperature is low, whereas on hot days the buildings provide shelter from the sun (Theeuwes, Steeneveld, Ronda, Heusinkveld, Van Hove & Holtslag, 2014). De Kruijf, Van der Waerden, Feng, Böcker, Van Lierop, Ettema & Dijst (2021) concluded an opposite effect for the relationship between temperature and e-cycling in the Netherlands. Higher temperatures decreased the probability of e-cycling, which is not in line with other studies. Similar to Helbich et al. (2014), De Kruijf et al. (2021) did find a that precipitation negatively influences the probability of cycling. Heavy precipitation increases the perceived risk of cycling, making it a less appealing mode option (Meng, Zhang, Wong & Au, 2016). Wind speed was also found to negatively affect the cycling probability (De Kruijf et al., 2021; Helbich et al., 2014). Although Helbich et al. (2014) concluded that wind plays a stronger role in more weather-exposed remote areas, Blocken & Carmeliet (2004) state an important downside of wind in urban areas with high-rise buildings. High-rise buildings catch the wind high up and move it downward along the building. This creates uncomfortable drafts and guts on street-level for cyclists and pedestrians.

Differences in results have been observed regarding the influence of the weather on cycling for different types of trips. Recreational trips appear to be much more influenced by weather conditions than utilitarian trips (Thomas et al., 2008). Helbich et al. (2014) analyze that utilitarian trips are often less flexible in nature and are more routine trips. These trips have to be carried out, regardless of the weather, and are therefore less impacted by the weather conditions. De Kruijf et al. (2021) researched the effect of the weather on the probability of e-cycling in commuting trips and found that it does influence the probability of e-cycling in commuting trips. Finally, the results of the study by Ton et al. (2019) have to be mentioned. Contrary to other literature, they found that weather is not relevant for the active transportation mode choice in the Netherlands. According to these researchers, this could be explained by the mild climate with frequent rain that is present in the Netherlands in combination with the bicycle being a common mode of transport.

Habit

According to Schneider (2013), as people develop routine choices, they may no longer be susceptible to information that could cause them to consider other transportation modes. In this case, the transportation mode choice has become a habit. Friedrichsmeier, Matthies & Klöckner (2013) support this statement by declaring that habits lead to stabilization of travel behavior over time, which is the result of a weakening of the influence of other predictors of the transportation mode choice. Furthermore, they claim that behavior frequency and context stability are the main contributing factors that result in habit. In terms of behavior frequency, it was found that the more often a certain behavior has been successfully performed in a stable context, the more determining it becomes for future behavior, whereas the influence of intentions and deliberate decision making becomes less. Regarding context stability, multiple studies concluded that habit strongly influences the transportation mode choice only when the context remains stable (Friedrichsmeier et al., 2013; Schneider, 2013; Verplanken, Walker, Davis & Jurasek, 2008). Verplanken et al. (2008, p. 122) define 'context' as "*the* *environment where behavior takes place. This may include the physical environment and infrastructure, but also spatial, social and time cues which instigate action*". Habit can be overcome by disrupting the stable context. A disruption in the stable context can be caused when people experience significant life changes, for example when they move to a new location (Schneider, 2013). This creates a window for change, and, especially in relation to transportation mode choice, people can be encouraged to use more sustainable transportation modes (Friedrichsmeier et al., 2013; Verplanken et al., 2008). Habit can be taken into account in policies and interventions to change travel behavior by identifying various sources that contribute to the creation of habit before the intervention, by targeting the groups of people that are not very strongly influenced by habit in their travel behavior, and by utilizing naturally occurring disruptions in the context (Friedrichsmeier et al., 2013).

Socioeconomic factors

Transportation mode choice partly depends on socioeconomic factors. Factors that are often found to be significant in the transportation mode choice are individual characteristics such as gender, age, education, employment status, income, and physical disabilities, and household characteristics, including household size, and household car ownership (Eldeeb et al., 2021; Schneider, 2013; Ton et al., 2019). Piatkowski & Marshall (2015) researched the influence of some of these socioeconomic factors on the probability than an individual will choose to cycle. Regarding the individual characteristics, they determined that men are more likely to cycle than women. Furthermore, a higher education was found to lead to higher odds of cycling, as was also confirmed by Ton et al. (2019). A higher income on the other hand was associated with a lower probability of cycling. For household characteristics, Piatkowski & Marshall (2015) concluded that an increase in household size results in an increase in the probability of cycling. Additionally, Piatkowski & Marshall (2015) and Eldeeb et al. (2021) both established that access to a car decreases the odds of an individual choosing to cycle. Ton et al. (2019), who conducted their research in the Netherlands, did not find significant relationships for some of the socioeconomic factors (including gender and age), whereas many studies do find significant results for these factors. Furthermore, the factors that were significant in the research of Ton et al. (2019) showed to be less important compared to the results of other studies. According to Ton et al. (2019), this could be due to the diverse cycling population in the Netherlands compared to other countries, where the majority of cyclists are younger males. Another explanation could be found in the theory of Schneider (2013), who suggests that socioeconomic factors do not directly influence the transportation mode choice, but affect each part of the decision process, and therefore are not necessarily significant when researched on their own. Although studies have found differences for the cycling probability between the levels of the socioeconomic factors, Piatkowski & Marshall (2015) claim that cyclists are treated as a homogenous group in the determination of policies and the creation of cycling facilities. They argue that, due to the differences, identifying populations that are more likely to change their travel behavior may be an important strategy for effectively impacting transportation mode choice.

2.3 Building Characteristics

Although not much research has been conducted on contribution of building characteristics on the willingness to cycle, various studies have been performed about the effect of building characteristics on people's perception and experience in general. From these studies building characteristics can be derived that might be play a role in the evaluation of the environment and therefore in the willingness to cycle. However, before the building characteristics can be collected an understanding is necessary of how people perceive buildings, especially while moving around, to determine which characteristics might stimulate bicycle use.

2.3.1 Perception of Buildings

Buildings in an environment are objective information about that environment. When looking at a street it can for example be stated that there are brick buildings of six floors present. This is objective information no one can argue against. However, the buildings can partly become subjective information when people place judgements on the buildings based on their perceptions. When people observe an object – in this case a building – they connect the image of the object to previous experiences. This causes people to attach certain feelings to an environment, even if they have never seen it before (Azma & Katanchi, 2017). Ma & Cao (2019) state that not only previous experiences, but also individual and social factors (e.g. gender, social class, culture, etc.) influence the way an environment is perceived. It is therefore possible that people with the same socio-demographic characteristics have different perceptions of the same environment. The visual perception of the environment and the subjectivities that come with it are determining for human behavior. How an environment is perceived affects people's actions, reactions, and feelings (Azma & Katanchi, 2017; Yammiyavar & Roy, 2019). In the context of transport decisions, this for example might lead to different choices regarding transportation mode or route.

Yammiyavar & Roy (2019) claim that perceptions of buildings are formed by the facades. A façade communicates the inside of the building to the outside. Based on previous experiences a person can connect subjectivity and feelings to a building. When for example a person sees a display window on the ground floor it is likely that a connection will be made with retail stores. The feelings that a person commonly experiences in a retail store will form a perception of the building without entering the building. The design of a façade can therefore influence the perception of the building. This is used as an advantage by architects, because the design of the façade can manipulate the perception to a desired perception.

Montoya, Horton, Vevea, Citkowicz & Lauber (2017) have studied the "mere exposure effect". This effect entails that the liking for a stimulus increases when a person is repeatedly exposed to that stimulus. People initially experience wariness and uncertainty when they are introduced to a new stimulus since they do not know what to expect. These feelings will decrease when on repeated exposure negative effects caused by the stimulus remain absent. When the number of exposures increases the positive effect of the stimulus will also increase. Connecting this effect to building characteristics would indicate that when people are more familiar with a characteristic as a results of repeated exposure the chances are higher that the characteristic will be seen as positive. However, at some point stimulus satiation is reached. Further repeated exposure will increase the amount of boredom caused by the stimulus and the positive effect from the stimulus will decline. This process is often described by an inverted U-shape distribution for liking (Montoya et al., 2017; Ng, 2020). Montoya et al. (2017) link the "mere exposure effect" and liking to recognition of a stimulus. There is a positive relation between liking and recognition when stimuli are presented only a limited number of times and for a short duration. This is explained by the low levels of conscious recognition that occur under these circumstances. According to these researchers conscious recognition is unnecessary and will speed up the stimulus satiation. Consequently, when the stimuli are presented more frequently and for a longer duration, increasing the conscious recognition, the liking will decrease. From this it can be derived that an environment should be diverse while still repeating stimuli at short intervals to increase liking due to repeated exposure, while at the same time preventing conscious recognition and satiation.

There are studies that consider the perception of buildings and the environment while traveling (Ma & Cao, 2019; Nasar, 1994; Olde Kalter & Groenendijk, 2018). There is a distinction between cars and public transport compared to pedestrians and cyclists when it comes to the perception of the environment while traveling. People traveling by car or public transport are more isolated from the environment because they are in vehicles and are traveling at a high speed. Pedestrians and cyclists on the other hand, are immersed in the environment at a low speed and get to hear, see, and feel what is happening around them. This more extensive experience results in a more detailed perception of the environment (Ma & Cao, 2019).

Olde Kalter & Groenendijk (2018) have looked into the influence of the environment on travel time perception among cyclists. They concluded that routes that people characterize as boring are perceived as longer. This is in all likelihood caused by the absence of enough stimuli. Routes that were characterized as attractive and diverse were found to have shorter perceived travel times. Nasar (1994) states that diversity in the environment can increase positive feelings due to the presence of enough stimuli. Too much stimulation on the other hand can lead to negative feelings. According to Gehl (2010) senses need stimulation every 4 to 5 seconds for reasonable balance between too little and too much stimulation. It can be concluded that the level of stimulation from the environment affects the perceived travel time and, as travel time is a determining factor for transportation mode choice, can therefore influence the transportation mode choice. Especially with regard to cycling, this would mean that when the perceived travel time for the bicycle is short, the chances are higher that the bicycle is chosen as a transportation mode. Thus, careful consideration of building design in relation to stimuli can affect people's perception of an environment and could influence their transportation mode choice.

2.3.2 Building Characteristics in Literature

Literature that examines the effect of building characteristic on the willingness to cycle (particularly in access trips to train stations) does not exist to the best of the author's knowledge. However, there have been various studies that have researched the effect of building characteristics on people in general and on the experience of the environment for pedestrians. These studies are used to identify potential stimulating building characteristics for the willingness to cycle, as both pedestrians and cyclists can be considered low-speed travel modes and are therefore comparable to a certain extent. The building characteristics that are collected from the literature are grouped into categories to make the list of characteristics more comprehensible. These categories – Building Height, Building Style, Building Function, Façade Openings, Complexity, Order, Materials, Maintenance, Edge Zone, and Other Factors – will be discussed in the next sections.

Building Height

Many studies report significant effects for the height of buildings in relation to the experience of the environment (Claxton, 2019; Gehl, 2010; Lindal & Hartig, 2013; Liu, 2021; Olde Kalter & Groenendijk, 2018). Gehl (2010) has extensively looked into the human-scale aspect when designing an environment. He states that how the environment is experienced depends for example on how much of the buildings people actually experience. The upper floors of high-rise can only be seen at a distance and never up close. According to Gehl (2010), the connection between street and building is effectively lost after the fifth floor. He states the positive effect of relatively low buildings by illustrating the situation in New York City. In Greenwich Village and Soho buildings are lower than in Manhattan in general. This allows for the sun to reach the streets, making the environment seem more attractive. This in turn invites people to spend more time outside, generating considerably more life in the streets than in the high-rise areas of Manhattan. This example shows what lower buildings can do for the way people experience an environment.

Liu (2021) researched preferences for cyclists traveling to a metro station and found that regarding building height cyclists prefer buildings with four to six floors. It has to be noted that this research was conducted in a large city in China, where high-rise is more common than in the Netherlands. This could influence the results based on the “mere exposure effect” explained in paragraph 2.3.1. Olde Kalter & Groenendijk (2018) concluded that Dutch cyclists find high-rise less attractive. Based on previous studies, Lindal & Hartig (2013) explain the lower attraction to high-rise by stating that the height of a continuous block of buildings along a street and the height of the buildings at the distal end of the street affect the sense of enclosure, which is greater for high-rise environments compared to low-rise environments. People prefer defined open spaces to highly enclosed spaces (Nasar, 1994).

Building Style

A building’s façade is the part of the building that can be seen from the street and consequently is the part cyclists associate most with the surroundings. The façade can provide context to an area and can display various building styles. Historic and modern building types can be considered as having a great differences in the general sense of character and the aesthetics particular to each type. Studies by Herzog & Shier (2000) and Ng (2020) found that people prefer modern buildings over older buildings. However, it has to be stated that when both modern and historic buildings were shown with similar physical conditions in terms of maintenance, older buildings were all of a sudden preferred. The preference for a building type therefore seems to rely on the level of maintenance. Lindal & Hartig (2013) say that entropy – or architectural variation – has a positive effect on the perception of an environment because it generates fascination. A street should therefore not consist of a singular building type. Over time, the design of buildings has shifted from design in urban context to unique individual buildings. According to Gehl (2010), these buildings are often meant to be seen from a distance and do not consider the human-scale on street level. Bond (2017) agrees and claims that the imperative to design a unique and individual building overrides the effect the building will have on its residents. Azma & Katanchi (2017) also warn that when buildings are designed individually and without attention for its surrounding buildings, the homogeneity of the urban view can be destroyed. When every building has an individual expressive design, a uniform appearance of urban space does no longer exist. Relating this to the perception of an environment means that there are too many stimuli and the environment will be evaluated negatively.

Building Function

When it comes to the function of buildings, studies have shown that a mix of different kinds of functions is preferred. Both Liu (2021) and Mo et al. (2018) have found that in an environment with mixed land use people are more prone to walk. The environment is more diverse and therefore provides a more interesting experience. Generally, people prefer buildings that are transparent in terms of function. The function of a building has to be visible from the outside (Azma & Katanchi, 2017).

Liu (2021) examined the preference for the amount of retail stores along the street. This resulted in the conclusion that pedestrians prefer 25% to 50% of the street front to be retail stores and cyclists prefer 50%. The higher percentage for cyclists is presumably caused by the increase of life in the street that comes with retail stores, which is linked to the appeal of a street for cyclists. Areas with mixed functions provide more activities in and near buildings, generating more life in a street. With for example both retail and residential functions present in a street, there is life at all hours of the day. During the day there is activity in the stores, and in the evening and at night there is activity in the houses. This increases the feeling of safety, which also increases preference. Many cities have even implemented ground-floor policies to create activity. An example is Melbourne, where it is required that 60% of the street façade of new buildings is open and inviting along major streets (Gehl, 2010).

Industry as a building function is regarded as negative (Nasar, 1994; Olde Kalter & Groenendijk, 2018). This has likely to do with the association with the mono-functional areas that are solely created for industry. Streets with mono-functional buildings that have no activity for the majority of the day are perceived negatively due to lack of diversity and activity (Gehl, 2010).

Façade Openings

According to Stamps (1999), one of the most likely design features to influence the perception of a building is the number of openings in the visual area of a building, or in other words the number of openings in the building façade. The most important opening is the entrance to the building. Herzog & Shier (2000) found that buildings with a visible entrance are preferred over buildings with no visible entrance. Yammiyavar & Roy (2019) confirm this. In their research, the visibility of the entrance door was repeatedly marked as a feature the respondents liked, whereas the inability to locate the entrance was marked as a feature they did not like at all. Yammiyavar & Roy (2019) state that one of the elements in a building façade that can create a positive perception is the entrance door and its characteristics (e.g. size and location). Gehl (2010) also mentions the presence of entrances as a factor to make the experience of the environment interesting. Furthermore, research by Gehl (2010) has shown that the openness of a façade can influence the behavior of passers-by. He found that open façades tend to slow down pedestrians because there is much to look at as opposed to closed façades where the walking speed was higher and people stopped less frequently. Closed and monotonous façades that have little detail can even influence the walking behavior to such an extent that people refrain from walking. In addition, Gehl (2010) claims that many doors and narrow units will intensify the experience and will therefore make traveling along the façades more interesting. The narrow units in terms of windows are contradictory the findings of Yammiyavar & Roy (2019), who found a liking for display windows, as they give a view of the interior of the building. Thus, a clear conclusion for the preferred size of windows cannot be drawn based on the reviewed literature.

Complexity

Many studies have looked into the effect of complexity on the preference for buildings (e.g. Akalin, Yildirim, Wilson & Kilicoglu, 2009; Herzog & Shier, 2000; Lindal & Hartig, 2013; Nasar, 1994; Ng, 2020). Complexity can be defined as the number of elements present in a scene, where there is noticeable difference between the elements (Lindal & Hartig, 2013). A building does not necessarily become complex solely by the number of elements, but also by the coherence of the elements. Regarding building façades, several elements can contribute to the degree of complexity. Various studies use surface ornamentation as one of the variables to express complexity (Herzog & Shier, 2000; Lindal & Hartig, 2013; Ng, 2020). Other variables that are used are the presence of columns in the façade and the level of detail (Gehl, 2010; Herzog & Shier, 2000). According to Gehl (2010), carefully designed building details can contribute to an interesting experience of the environment. Furthermore, his research showed that pedestrians profoundly appreciate the details in a façade while walking. These complexity variables and complexity in general are sometimes also referred to as the visual richness of a façade. Herzog & Shier (2000) found that buildings that are high in visual richness are preferred over the ones low in visual richness. This result indicates that high complexity is preferred over low complexity in building façades.

Complexity does not always come from complicated details, but can also be created by combining simple lines and shapes in intricate and unexpected ways (Ng, 2020). Ikemi (2005) states that the diversity of elemental shapes can add to the degree of novelty people experience when looking at a façade. Novelty is closely related to complexity, as they both spark interest by creating designs that encourage exploration and can provide a large number of stimuli. Lindal & Hartig (2013) state that perceived complexity may differ when evaluating a building block as a whole as opposed to evaluating individual buildings.

In general, studies agree that the degree of complexity is a determining factor in the preference for buildings and that increased complexity can increase preference (Akalin et al., 2009; Bond, 2017; Herzog & Shier, 2000; Lindal & Hartig, 2013; Nasar, 1994). Herzog & Shier (2000) have further looked into the effect of preference due to complexity in modern and older buildings. They found that though in general modern buildings were preferred over older buildings, as modern buildings became more complex they lost their preference advantage over older buildings of similar complexity.

Order

Research has found that people notice the façade of a building more than the massing or space of a building. It is therefore in the façade that order or complexity can be achieved that influences the perception of an environment (Nasar, 1994). In relation to building façades, order is often described as the degree to which a façade hangs together or the organization or patterns that can be found in a façade. Another term that can describe order is the level of coherence (Herzog & Shier, 2000). An increase in the degree of order in a façade decreases interest, but will increase preference (Nasar, 1994). Order is closely related to complexity. High levels of complexity often go hand in hand with low levels of order. Though it has already been stated that complexity can increase preference, there still has to be an adequate level of coherence to make the façade legible (Ng, 2020). Moderate levels of complexity combined with a high degree of order will generate high preferences (Nasar, 1994). According to Ng (2020), older buildings are perceived as more organized than modern buildings. Modern buildings often combine lines and shapes in intricate and unpredictable ways, making the buildings seem more complex. In contrast, older buildings are often finely decorated, have uniformity in the materials, and display symmetry in the façade, which makes them appear more organized. Multiple studies have mentioned symmetry as a factor that can create order (Ng, 2020; Stamps, 1999; Yammiyavar & Roy, 2019). Stamps (1999) found that symmetry can reduce the judged complexity of a façade by approximately 25%. Furthermore, he determined that horizontal symmetry has a greater effect on the reduction of judged complexity than vertical symmetry.

The use of horizontal and vertical elements has been mentioned by Stamps (1999) and Gehl (2010) as factors that influence the visual quality of an environment. Based on Gehl's (2010) research, vertical elements in a façade can make distances seem shorter and can make the experience more interesting, whereas horizontal elements can make distances seem longer and more tiring. The horizontal and vertical elements can also be used to create patterns in the façade. Repeating patterns not only contributes to the degree of order, but also can make the experience of the environment more interesting by creating a rhythm in the façades (Azma & Katanchi, 2017; Gehl, 2010; Nasar, 1994).

Another factor that is mentioned in relation to order is contrast in the façade. Examples of variables that can create contrast are the use of curved lines or forms, the variation in depth of the exterior walls, the number of vertices in the façade, and whether or not the volume of the building is broken up (Herzog & Shier, 2000; Stamps, 1999). As reported by Nasar (1994), low contrast between façade elements or between building and surroundings creates order. Low contrast has also been named as one of the key variables preferred in urban street scenes.

To conclude, Ng (2020) best describes the relation between order, complexity, and preference by stating that diversity and complexity create interest in the environment, while order, including symmetry and repetition, has to be present to keep the interest within tolerable limits.

Materials

Azma & Katanchi (2017) studied the appearance of a singular building in relation to the urban space. They found that if a building is designed without attention for its surrounding buildings, the uniform appearance of the urban space can get lost. Variables that they have taken into consideration in their analysis were the color variation and the texture of the buildings. These factors contribute to the aesthetic of a building and the environment (Nasar, 1994). The materials that are used in the construction and façade of a building can influence perception. For example, contrast in materials can create complexity, whereas uniformity in materials can make buildings look more organized (Ng, 2020). However, Modernist buildings for example were often constructed with identical materials from the ground floor all the way to the top and with the same level of detail throughout the building. Despite the organized look of these buildings, the uniformity in materials can also make the appearance of the buildings uninteresting (Gehl, 2010).

The type of material is often linked to the time the building was constructed in. Old-style buildings are often constructed with natural materials, as opposed to modern-style buildings that are constructed with man-made materials (Ng, 2020). According to Nasar (1994), natural materials are often preferred as they might contribute to a feeling of relaxation. Following his study, artificial elements should be removed or buffered with nature.

Van de Kuil (2017) specifically mentions the façade materials that are to be researched in her study, which are concrete, brick, and glass, as these are the general materials associated with the façade types she included in her research (industrial, historic, and modern façades). However, she later excluded the variable from her research due to a significant correlation between the materials and the façade type variable. This correlation seems logical as it was found that the material type is often related to the time period in which a building is constructed.

Maintenance

Herzog & Shier (2000) have found a relation between preference and building age. However, they concluded that this relation depends on the level of building maintenance. In their study, preference was positively correlated with maintenance, indicating that a higher level of maintenance will lead to higher preference. Azma & Katanchi (2017) report neglected façades as a factor that affects the visual quality of an environment, supporting the relation between maintenance and preference. Building age on the other hand was negatively correlated with maintenance, which means that when the age of a building goes up, the level of maintenance goes down, and consequently preference goes down. This relationship is backed by Ng (2020), who established that modern buildings are preferred over older buildings if maintenance is not controlled in the experiment. If maintenance is controlled and older and modern buildings are presented with similar physical conditions, the opposite result is found. Older buildings are now preferred to modern buildings. Finally, Herzog & Shier (2000) mention two factors that influence the perceived level of maintenance of a building. They state that fancy windows can enhance the perceived maintenance, whereas texture variation in the building façade negatively influences the perceived maintenance.

Edge zone

As defined by Gehl (2010, p. 82), "*the edge zone is the most active outdoor area in a residential area. Here are front doors – the exchange zone between private and public spheres – and this is where the activities from the residential areas move out to the terrace or front garden, in good contact with public space*". Although this definition gives a clear indication of what the edge zone entails, it is not necessarily limited to residential areas. More generally described, the edge zone is the zone pedestrians see and experience when they walk through an area and the zone where indoor and outdoor life can interact. In terms of building characteristics, this is the interaction zone between building and street.

How the edge zone is treated has a significant influence on life in an area. Commonly a street with life and activity will be chosen by pedestrians and cyclists over a deserted street. The activity in the street will not only make a trip more interesting, but will also make the chosen route feel safe (Gehl, 2010).

A factor that considerably affects the life in an edge zone is the (semi-private) outdoor space directly in front of a building's ground floor. To create a link between the inside and outside of a building the implementation of a transition zone with soft edges between public and private is imperative. This can be achieved by for example changes in pavement, height differences, steps, and furniture (Gehl, 2010). An example of furniture that positively impacts the perception of an environment and simultaneously creates a distinctive link between the inside of the building and the street is the presence of terraces in the edge zone (Azma & Katanchi, 2017; Gehl, 2010; Olde Kalter & Groenendijk, 2018). The function of the ground floor of the building is immediately visible and people using the terrace creates life.

Furthermore, Gehl (2010) states that also the landscaping and greenery in front of buildings can contribute to an interesting experience of the environment, while at the same time creating a soft edge for the transition zone. Liu (2021) observed a preference for more street-side greenery and found that cyclists are even more sensitive to the presence of greenery than pedestrians.

Other Factors

A few other factors were mentioned in literature that could be stimulating bicycle use, but these were more difficult to categorize and were often not discussed extensively. The first factor is the viewing distance – i.e. from how far away a building is seen (Herzog & Shier, 2000; Stamps, 1999). Although Stamps (1999) does not clearly state the influence of viewing distance on the perception of buildings, Herzog & Shier (2000) conclude that far views are preferred over near views.

Ikemi (2005) found that mystery surrounding a building can enhance preference. One of the factors that contributes to mystery is shadows. Shadows can indicate that part of a building is concealed, leaving the actual look of the building up for suggestion. Nasar (1994) also mentions that shadows can influence how buildings are perceived.

Lindal & Hartig (2013) state that the roof type, and more specifically the roofline silhouette, has an influence on the perception of an environment. They claim that the roofline silhouette is related to complexity and building style and found that higher levels of variation in the silhouette positively influence the evaluation of an environment.

Finally, Gehl (2010) has extensively argued the importance of the ground floor of buildings for the level of activity. In addition to all factors that were mentioned previously, the last factor that can increase activity in the street positively is the use of short units – or short façades. Short units help create enough stimuli to keep the environment interesting. The length of a façade can therefore influence the experience of the environment.

2.4 Conclusion Literature Review

The literature review consisted of three parts, each part related to a research question as defined in paragraph 1.2. The first two parts served to acquire the necessary background information on access trips, and transportation mode choice, with particular attention for the choice for the bicycle. The conclusions for these two parts are discussed in paragraph 2.4.1. The third part of the literature study focused on people's perception of buildings in general and while traveling, and the building characteristics that might stimulate bicycle use. This will be discussed in paragraph 2.4.2.

2.4.1 Conclusion

The first two parts of the literature review provided the answers to the first two research questions. Therefore, the conclusions for these parts will be given by answering these questions.

1. What are access trips in train journeys?

An access trip in a train journey is the first part of a multimodal journey where the train is the transportation mode used in the main part of the journey. This first part is the trip from a starting point (often the traveler's home) to the train station. The access trip usually requires a different transportation mode than the mode used for the main part of the journey. It was found that better access trips to train stations can improve the overall satisfaction with a train journey. Improving the access trip can be achieved by enhancing the accessibility to the train station for sustainable transportation modes and by making the routes to the train station more human-scaled and appealing. Consequently, the improved access trips can persuade people to travel by train more often.

2. Which factors influence transportation mode choice and particularly the choice for the bicycle (in general and for access trips in train journeys)?
For the transportation mode choice in general, people consider the modes that are available to them and are feasible for their trip purpose. They further contemplate the safety aspects related to the possible transportation modes, the money, time, and effort necessary to conduct the trip with a certain transportation mode, and they take into account the direct personal benefits the transportation mode offers them. Finally, people tend to choose a transportation mode based on habit.

Regarding the transportation mode choice for the bicycle, various factors have been identified in the literature that have an effect on the decision to cycle: the availability of cycling facilities, the comfort level, the effort required, the presence of greenery, safety levels, the travel time, the weather, and the integration of the bicycle with the train. The availability of the bicycle can be increased by enhancing cycling facilities such as bicycle paths and bicycle parking. Furthermore, in the design of cycling facilities the level of comfort has to be taken into account. Roads with poor topography increase the effort for cyclists, which decreases the level of comfort. For a good level of comfort it is advised to create direct connections for cyclists between roads, away from motorized traffic, and provide them with well-maintained bicycle paths. Greenery is also beneficial for the feeling of comfort. However, the amount and placement of greenery has to be regulated, because it can also make people feel unsafe. Safety is often considered a problem for cyclists. The level of safety can be improved by building separate bicycle paths and implementing traffic calming measures. In short, bicycle use can be increased if an environment is provided that is suitable for cyclists. Furthermore, travel time has a significant influence on the decision to cycle. The travel time for cycling is often over-perceived. The objective travel time of cyclists can be reduced by for example creating cycling highways and favoring non-motorized traffic at traffic lights. The perceived travel time can be reduced by creating attractive cycling environments. The weather, particularly the temperature, precipitation, and wind speed, can also affect the choice to cycle. However, this effect appears to be significantly less in densely built environments, where buildings provide shelter from the weather conditions.

For increasing the combination of bicycle and train use, it is beneficial to integrate cycling with train travel by providing bicycle parking at train stations and giving people the option to take their bicycle with them on the train. This will ease the transfer between the bicycle and the train, which makes train travel more appealing.

Finally, many studies have found differences in the decision to cycle for various socio-economic factors. In current practice, cyclists are often considered to be a homogenous group, while these differences in socio-economic factors in relation to cycling indicate that policies and interventions should focus on the differences between groups of cyclists.

2.4.2 Relevant Variables for Study
People's perceptions can influence their behavior. Regarding buildings, literature suggests that the perception is formed by the building façade and careful design can influence the perception. Characteristics that are familiar and are not associated with negative feelings should be repeated to increase positive feelings towards an environment. However, there should be enough diversity to prevent stimulus satiation caused by over-exposure. To encourage cycling attention should be paid to the level of detail in the buildings, as various sources state that more details are visible at lower speeds. Thus, careful consideration of

building design in relation to stimuli can affect people's perception of an environment and consequently their behavior. Therefore, the way buildings are designed can contribute to the transportation mode choice.

The literature review resulted in an extensive list of building characteristics that can influence a person's perception of the environment (see appendix A). However, not all characteristics have the potential to stimulate bicycle use and a selection was made of the building characteristics that appear to have the most potential. In this selection, characteristics that are to a certain extent similar are combined into one characteristic.

3. Which building characteristics have the potential to stimulate bicycle use (in general and for access trips in train journeys)?
The building characteristics that are potentially stimulating for bicycle use are listed in Table 1. Because the literature review suggests that a perception is formed through the building façade, the potential building characteristics included in the table are present in or visible when looking at the façade. The list of characteristics is still quite long, and a smaller number of characteristics will be selected for the research based on the research method that will be used.

TABLE 1 POTENTIALLY STIMULATING BUILDING CHARACTERISTICS FOR BICYCLE USE

CATEGORY	**CHARACTERISTIC**
BUILDING HEIGHT	Number of floors
BUILDING STYLE	Architectural variation
BUILDING FUNCTION	Function diversity
	Transparency
FAÇADE OPENINGS	Entrance
	Number of openings
	Size of openings
COMPLEXITY	Ornamentation
ORDER	Symmetry
	Variation in depth
	Vertical/horizontal elements
MATERIALS	Color
	Texture
	Uniformity
MAINTENANCE	Physical condition
EDGE ZONE	Activity
	Height differences in transition zone
	Furniture
	Greenery
OTHER FACTORS	Viewing distance
	Roof type
	Length of façade

3. Methodology

Various studies have addressed the influence of characteristics of the environment on transportation mode choice, and particularly the choice for the bicycle. However, despite buildings being a large portion of the environment, studies that research the contribution of building characteristics to the willingness to cycle are rare. In paragraph 2.1 it was explained that by improving the access part of a train journey, more people are likely to switch their transportation mode from car to train, which reduces greenhouse gas emissions. Therefore, there is a need for a better understanding of the factors that influence the access part of a train journey. To add to this understanding, this research examines the contribution of building characteristics to the willingness to cycle in access trips to train stations.

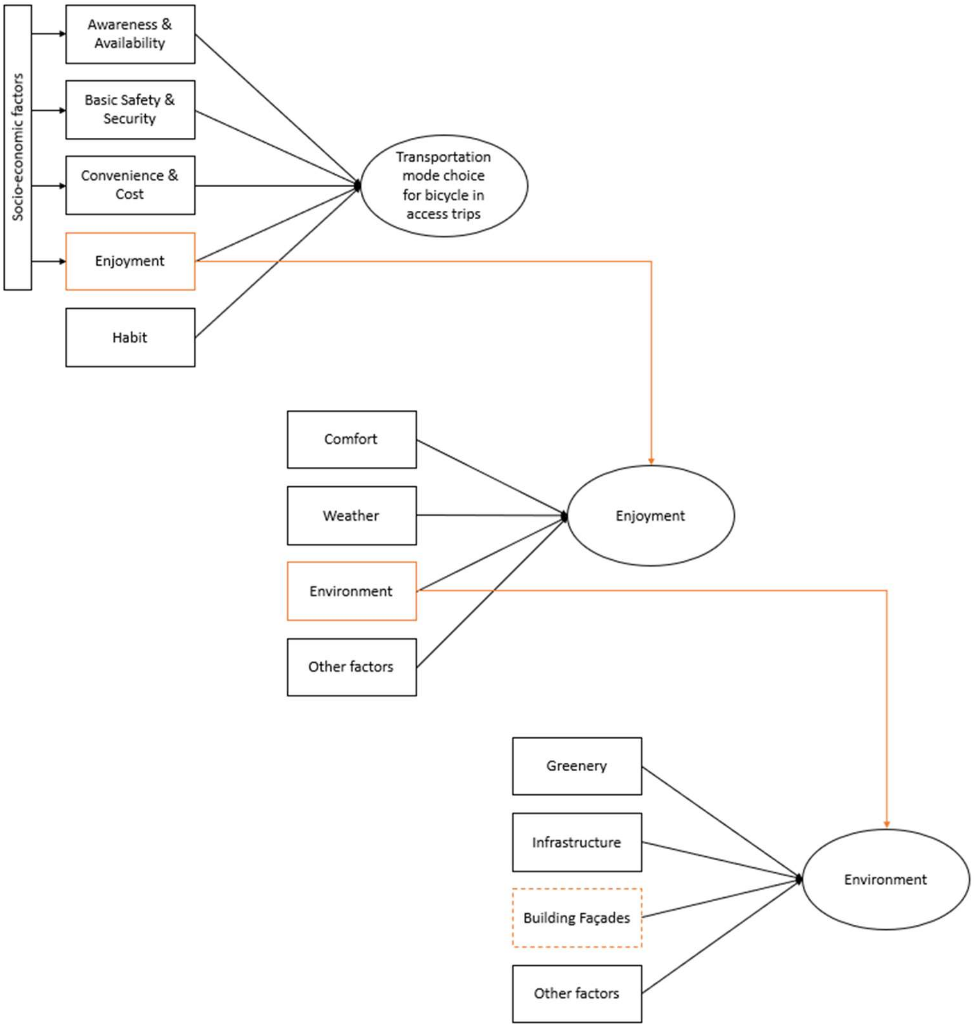

FIGURE 7 CONTEXTUAL MODEL RESEARCH CONTEXT

The research problem can be conceptualized in a model to help understand the context of the problem. This model can be seen in Figure 7. In the literature five steps were identified that determine the transportation mode choice of an individual. These steps also apply for the transportation mode choice for the bicycle in access trips. The step 'Enjoyment' can be further researched to determine what it entails. The aspects that were examined in the literature review are 'comfort', 'weather', and 'environment'. There are other factors that also determine ‘Enjoyment’, however, these were not addressed in the literature as this research focuses on the influence of the environment. The environment is made up of greenery, infrastructure, and other factors. What was concluded to be missing in the literature is the contribution of buildings and their characteristics to the experience and perception of the environment. Building façades appear to have the largest influence on the perception of the environment and it is hypothesized that building characteristics related to the façade contribute to the willingness to cycle through their influence on the environment and consequently on ‘Enjoyment’.

In the literature several building characteristics related to building façades were identified that potentially contribute to willingness to cycle. These characteristics were categorized and are conceptualized in the model displayed in Figure 8.

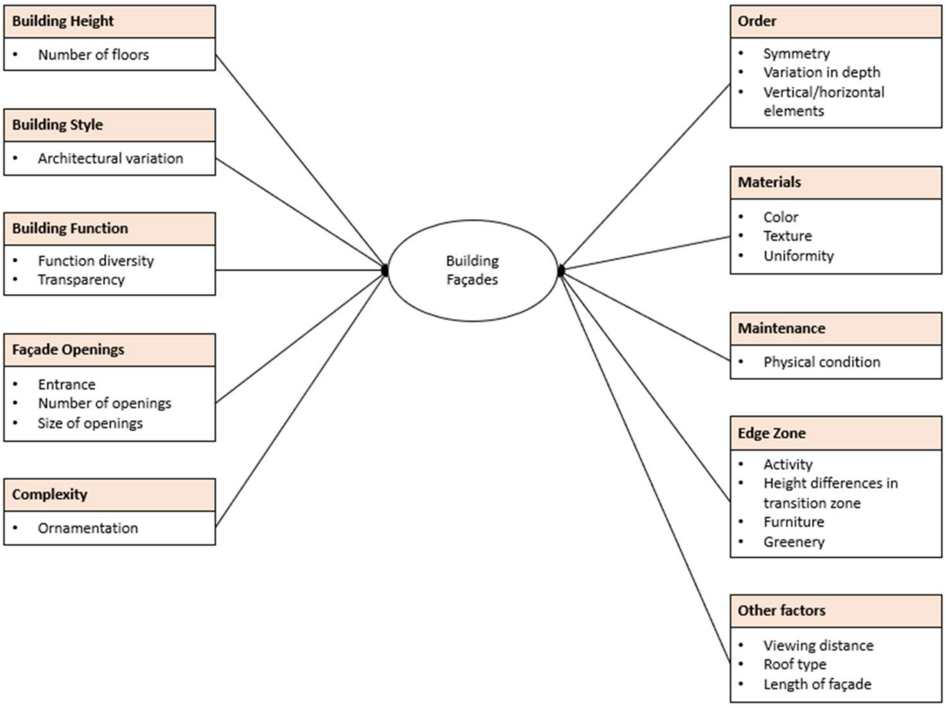

FIGURE 8 CONCEPTUAL MODEL

The remainder of this chapter will explain the methodology of the research. First, methods to measure preferences are described. In paragraph 3.2 the steps for setting up the stated preference experiment are elaborately reported. This followed by the reasoning for the presentation method of the attributes in paragraph 3.3. Paragraph 3.4 explains the choices that were made regarding the visualization of the attributes. The following two paragraphs describe how the survey, in which the stated preference experiment is implemented, is set up and how data is collected and processed. Paragraph 3.7 discusses the models that will be used for the analyses of the preference data. Finally, the chapter is summarized in paragraph 3.8.

3.1 Measuring Preferences

People make choices every day. In order to make a choice people consider various alternatives. The alternative that is chosen is determined by personal preferences of the decision-maker. The outcome of the choice situation can be determined by the observation of the action (behavior) that followed the choice. However, the underlying reasoning for why a person made that particular choice is often difficult to identify. The reasoning process of a person in a choice situation can be investigated by measuring that person's preferences. However, measuring one person's preferences and generalizing the results to a larger population is inaccurate. This approach does not take into account the variability in the reasoning underlying choices made by multiple individuals. The variability in the reasoning underlying choices (i.e. variability in preferences) is also referred to as 'heterogeneity'. Preference analysis tries to explain the variability in preferences across a sample of multiple individuals, or in other words, it tries to explain the heterogeneity in preferences (Hensher, Rose & Greene, 2015).

Choices can be predicted by measuring people's preferences. Preferences are measured through 'sources of preference' (Hensher et al., 2015). The sources of preference are the reasons people prefer one alternative over another. A source of preference in the context of transportation mode choice is for example 'travel time'. A person can prefer the car over other transportation modes because it has a shorter travel time.

According to Hensher et al. (2015), once the sources of preferences have been identified they have to be measured in units that allow comparison of various combinations of the attributes across the alternatives. Based on evaluations of the alternatives by individuals, a numeric score can be assigned to the alternative for an individual. This score is called the 'utility' of the alternative for said individual. An underlying theory for preference analysis is the Utility Theory. This theory operates under the assumption that individuals will base their choice on the utility of each alternative. This theory will be further discussed in paragraph 3.1.5.

There are various methods that can be used to collect preferences. The most important methods – rating, ranking, and choosing – are discussed below.

3.1.1 Rating

In the rating method, respondents are asked to rate an alternative according to a pre-specified scale. For this measurement scale, it is expected that individuals value each step on the scale equally. Each alternative is measured separately. Often, instead of alternatives, attributes are presented individually for evaluation. This can be considered problematic, as with this rating method the trade-off between attributes is not captured (Wijnen, Van der Putten, Groothuis, De Kinderen, Noben, Paulus, Ramaekers, Vogel & Hiligsmann, 2015). Wijnen et al. (2015) found that by individual presentation of the attributes respondents have the tendency to rate all attributes more equally and the differences in preference between the attributes are more difficult to determine.

3.1.2 Ranking

In the ranking method, respondents are presented with a set of alternatives and are asked to place them in order from least to most preferred (or vice versa). Ranking is a method that provides relative preferences, meaning that the outcome states that option A is preferred over option B, but it is not possible to assign a numerical value (utility) to the alternatives. Therefore, ranking is known as ordinal measurement as it only provides a scale from least to most preferred alternatives (Hensher et al., 2015).

3.1.3 Choice Experiments

The choice process and the resulting choice are often researched using a choice experiment. In a choice experiment, participants are presented with a set of two or more alternatives and choose the alternative that they prefer most. In the experiment the alternatives will be reviewed either as ‘chosen’ or ‘not chosen’, depending on the participants choice. The observed choices in combination with the utility theory make it possible to predict the choice between alternatives (Hensher et al., 2015).

Preference data can be collected using a revealed preference experiment or a stated preference experiment. Revealed preference experiments collect choice data in and from real world situations. This data is for example collected by tracking the trip a person undertakes using GPS. This provides the researcher with actual decisions made concerning e.g. mode and route choice, giving the data high validity. The data, however, only includes attributes that are present in the environment where the data is collected. Consequently, there is little control over the attributes that are provided in the dataset. When using a revealed preference experiment the understanding of choices is often limited to comprehension within the existing environment (Louviere, Hensher, Swait & Adamowicz, 2000). Moreover, the underlying reasoning why a person makes a certain choice over another is often unclear.

Stated preference experiments on the other hand, are a way of collecting data on people’s choices in hypothetical situations. Multiple choice options are given for situations that might exist or are proposed (Louviere et al., 2000). There is more control over the attributes that are included in the research. Stated choice data can also be used to find preferences regarding attributes (Hensher et al., 2015).

3.1.4 Decision on the Experiment

There has not been much research concerning the environmental aspects of a cycling trip to a train station, and specifically the contribution of building characteristics on choices made for these trips. With a revealed preference experiment it might be possible to determine the preferences regarding building characteristics on cycling routes based on route choice and the characteristics of those routes. However, more factors play a role in the route choice (e.g. travel time, obstacles such as traffic lights or slopes) and because the underlying reasoning for a route is not known it is difficult to determine the effect of solely building characteristics on the choice. Another aspect that is missing is the transportation mode choice process. The revealed preference data shows the transportation mode a person has chosen, but does not consider the decision process that happens prior to the trip and the factors that were taken into account. In the experiment it has to be possible to put the focus on the relationship between building characteristics and the willingness to cycle. A revealed preference experiment would therefore not suffice to reach the goal of this research. A stated preference experiment provides the control of and focus on variables that are necessary to measure preferences for building characteristics along a cycling route in relation to the willingness to cycle. The experiment in this research will provide the respondents with a rating task for each alternative instead of a choice task. Consequently, respondents are asked to evaluate only one alternative per question. This decision was made based on the presentation method of the attributes in the experiment, which will be explained in paragraph 3.3. Presenting respondents with a rating task lowers the burden of filling in the survey compared to a choice task. Nevertheless, the setup of the rating experiment will follow the general setup of a stated preference experiment. This provides the necessary control over the variables and the ability to test trade-offs between the attributes.

3.1.5 Utility Theory

When put in a choice situation, some individuals will make a different choice than others based on their preferences. They will choose the option that has the highest preference (or utility). Behavior based on the highest preference is also called 'utility-maximization' and is usually assumed in preference models (Train, 2002). These preferences relate to the characteristics, or in other words attributes, of the given options. Train (2002) states that holding some attributes 'fixed' in a preference experiment makes it possible to determine the utility of the 'non-fixed' attributes. It has to be kept in mind that there might be factors that are not included in the experiment but that do influence the choice for an option and are considered 'fixed' by the respondent. The utility U_{iq} for alternative i by individual q can be described by the sum of the observed value for utility V_{iq} and the random component ε_{iq}, which expresses the unobserved utility (Louviere et al., 2000). This is shown in equation 1.

$$U_{iq} = V_{iq} + \varepsilon_{iq} \tag{1}$$

Because in every situation there is an unobserved utility value, the observed utility value V_{iq} is never equal to the alternative utility U_{iq}. However, the unobserved utility factor is unknown and is therefore treated as a random factor. The observed utility V_{iq} for alternative i can be defined as a function of k variables x_{iqk} with associated parameter estimates β (Hensher et al., 2015), as shown in equation 2.

$$V_{iq} = f(x_{iqk}, \beta) \tag{2}$$

Hensher et al. (2015) follow this equation by stating that equation 2 is often simplified to a linear function for the observed utility. In equation 3 the observed utility V_{iq} is defined as the sum of the parameter estimates β_k multiplied by the attribute variables x_{iqk}.

$$V_{iq} = \sum_{k=1}^{K} \beta_k x_{iqk} \tag{3}$$

The individual q compares the utility of alternatives to determine which alternative yields the highest utility, and therefore which alternative they will choose. The utility of each alternative is known to the individual but not to the researcher. However, the researcher can calculate the probability that the individual will choose alternative i instead of alternative j by the following behavioral model (Train, 2002):

$$P_{iq} = prob(U_{iq} > U_{jq} \; \forall \, j \neq i) \tag{4}$$

3.2 Setting up the Experiment

As explained in paragraph 3.1.4, a stated preference experiment will be conducted for this research. This section describes how the experiment is created following the principals of an experimental design. In an experiment the effect upon one output variable can be observed given the manipulation of the levels of one or more other input variables. The manipulation of the attribute levels does not happen randomly, but occurs through an efficient experimental design. Inefficient designs can lead to biased or erroneous data sets, which are not desirable for the research outcome and should be prevented. Hensher et al. (2015) describe an 8-step process to generate stated preference experiments. This process is displayed in Figure 9 and is used as a guide for setting up the experiment. The details of each step will be explained in the following paragraphs.

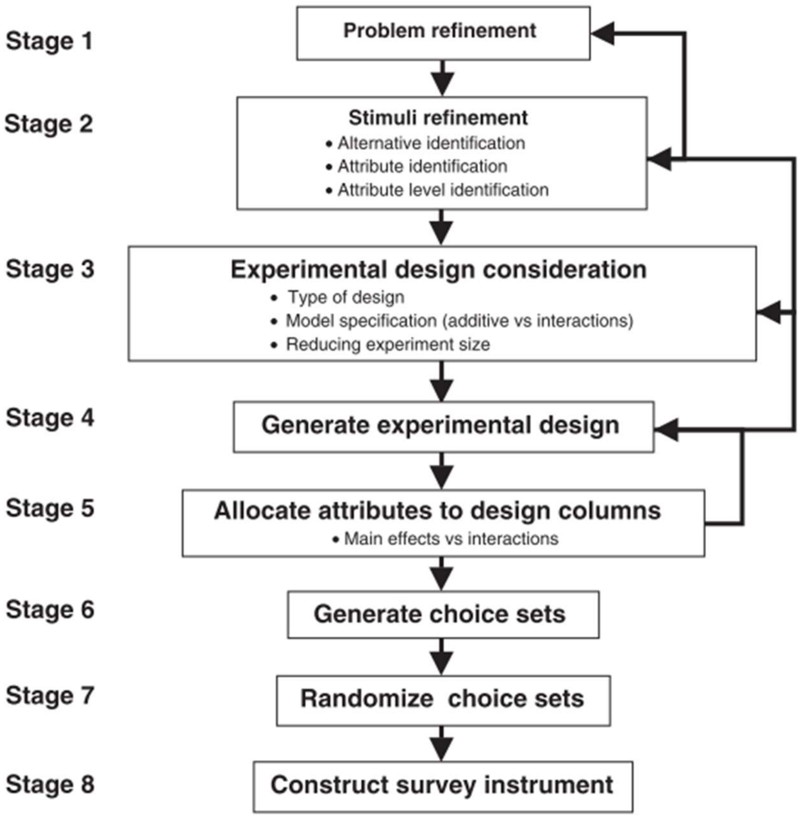

FIGURE 9 EXPERIMENTAL DESIGN PROCESS FOR A STATED PREFERENCE EXPERIMENT (HENSHER, ROSE, & GREEN, 2015)

3.2.1 Problem Refinement

To conduct a viable research, it is important to first have a clear understanding of the research problem. According to Hensher et al. (2015) the researcher has to start by asking the question *"Why is this research being undertaken?"*. By answering this question first, irrelevant research questions can be avoided. The research questions applicable to this research have been stated in paragraph 1.2. The first three research questions have been answered in the literature review of chapter 2. The answers to these questions provide the background information and theoretical framework for this research. The next step is to implement the potentially stimulating building characteristics that were identified in the literature in an experiment to investigate their contribution to the willingness to cycle. This contribution will be researched for cycling to the train station and cycling in general to test if there are differences between the two in which building characteristics stimulate bicycle use. Further, it will be examined how the building characteristics affect the experience of the environment. When the environment is more attractive it can reduce the perceived travel time of cyclists, and consequently, can contribute to the decision to cycle. It is therefore useful to examine which building characteristics improve the attractiveness of the environment and which building characteristics have a negative effect. Furthermore, it was found in the literature that people are more likely to choose the bicycle as their transportation modes if the environment is perceived as suitable for cyclists. Because of this, it is interesting to know if building characteristics can add to the perceived bicycle-suitability of an environment. To investigate how building characteristics can contribute to the experience of the environment, the effect of building characteristics on the attractiveness and bicycle-suitability will also be researched.

Based on this, the experiment can be viewed as focusing on two parts: a 'cycling' part and an 'experience of the environment' part. These can be further divided into the dependent cycling-variables and the dependent experience-variables that are to be researched. This division can be seen in Figure 10. The setup of the research will be further explained in the following paragraphs, but this divide means that four questions will be asked for each preference situation to be able to investigate all four dependent variables.

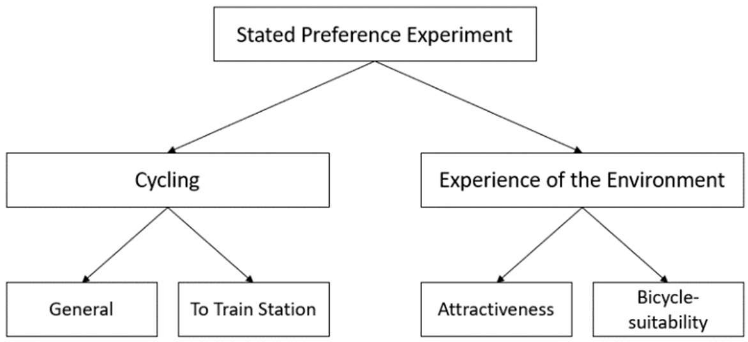

FIGURE 10 DIVISION OF THE DEPENDENT VARIABLES

3.2.2 Stimuli Refinement

The second step in the experimental design process is to refine the stimuli. In this step, first the alternatives of the experiment have to be identified. An 'alternative' in this research is a specific environment in which a cyclist moves. According to Hensher et al. (2015), respondents should be able to choose from a universal but finite list of alternatives. Every possible alternative has to be identified in order to achieve maximum utility for the alternatives. Leaving an alternative out of the list will lead to a threshold on the utility-maximizing outcome. The stated preference experiment will be unlabeled, with generic names for the alternatives ("profile 1/2/etc."). Attention has to be paid to the consequences of labeling alternatives. When attaching a label to an alternative, the label can become some form of extra attribute. People will relate some type of value and characteristics to a name based on the knowledge and experience they have with that name, possibly causing correlation between the alternative name and the actual attributes describing the alternative (Hensher et al., 2015). By using an unlabeled experiment, the alternatives will be viewed neutrally, bringing back the focus to the actual attributes for evaluation of the alternative.

The next step is to define the attributes that will be included in the experiment for every alternative. These attributes are the means to describe the alternatives. Because an unlabeled experiment is used, each alternative consists of the same attributes. The attributes are the building characteristics this research intends to look into and are determined based on the literature. In choosing the attributes, Hensher et al. (2015) warn about ambiguity and correlations between the attributes. For reliable results, this should be avoided. The full list of possible attributes gathered from the literature is shortened by merging or excluding attributes that are quite similar to avoid strong correlations. The attributes on the shortened list are then judged by the researcher and two experts in the field of mobility on relevance for the study. This resulted in a list of 12 attributes. These attributes were again examined for correlations and the ability to model the attributes was taken into account. A few potential attributes would be difficult to observe at cycling speed or would take too much time to model within the timeframe of this research. From the list of attributes that was identified in the literature to be potentially stimulating bicycle use, eventually six attributes were chosen for the experiment that seem sufficiently independent of each other and are modellable. These attributes can be found in Table 2.

After the attributes have been determined, attribute levels have to be assigned to each attribute. The number of levels for each attribute has to be considered attentively. When two levels are used, it can only be concluded that the relationship in terms of utility between the attribute levels is linear. When using three or more levels non-linear relationships can be observed. For each attribute it was chosen to use three levels to keep the design and creation of the simulations feasible. Although with three levels the true understanding of the relationship that exists between the levels cannot always be observed, it will provide sufficient knowledge of a good approximation of the relationship and it is beneficial for a balanced experimental design (Hensher et al., 2015). Another point that is important is the range of the levels. It is preferred to maximize the end-points of the levels, however, realism of the levels for the respondents has to be kept in mind as well as the ability to notice the differences in the attribute levels. Table 2 shows the attributes that are chosen for the experiment, along with their assigned levels.

TABLE 2 ATTRIBUTES AND CORRESPONDING LEVELS

Attribute	Levels
Building Height	2 floors
	4 floors
	6 floors
Building Type	100% historic buildings
	50%-50% historic/modern buildings
	100% modern buildings
Openness of Façade	Closed façade
	Semi-open façade
	Open façade
Front Garden	Absent
	30 cm
	1.5 m
Distance to Building	2 meters
	4 meters
	6 meters
Activity of Ground Floor	Little traffic
	Moderate traffic
	Much traffic

In this experiment every alternative consists of six attributes each with one of three levels. The attributes and levels will be modelled in simulated environments to communicate them to the respondents, a decision that will be further explained in paragraph 3.3. First of all, the **height** of the buildings is included. The levels that are assigned to this attribute are based on observations in the Netherlands and the ability to communicate the different heights properly in the simulated environment. Although in the Netherlands enough buildings can be found that are higher than 6 floors, this did not translate very well into the simulation. For all buildings of 6 floors or higher the difference in height was not noticeable enough because of the fixed viewing point of 175 cm above the ground. Next, **building type**, or in other words the variation in the architecture of the buildings, was included. There are many types of architecture, but the decision was made to choose two clearly distinguishable building types and include a mix of the two as another level, since literature suggests that people respond best to variation. The levels for **openness** of the façade were based on observations in the Netherlands. References for the gradation of the levels were industrial buildings, which often have limited or no windows, residential buildings, which have windows on the ground floor, but small enough so passers-by cannot see everything that goes on inside, and retail buildings, which have large open façades so the merchandise can be seen from the outside. The attribute **front garden** was included as this is a common phenomenon in the Netherlands. In cities buildings often have no front garden or a front garden as wide as a pavement tile. In more spacious neighborhoods the front gardens are often larger. The next attribute that was included is the **distance** from the bicycle path to the building. The levels go up from a very short distance to a large distance, since literature suggests that people feel enclosed by narrow streets and more at ease in broad streets. Lastly, the **activity** of the ground floor was added. This is the amount of pedestrians, cyclists, and cars present in the street. The levels range from little traffic to much traffic.

There are more attributes that influence the dependent variables that have to be included in the simulated environments to make them realistic. However, since these are not attributes that will be investigated they will have fixed values across all alternatives. First of all, the layout of the majority of the infrastructure is fixed in all environments. The **road** and **bicycle path** have the same measurements for every alternative. Although literature states that these attributes could affect the willingness to cycle, this research does not consider them in the experiment as they are not related to building characteristics. Furthermore, the **bicycle velocity** is fixed at 15 km/h. This was done so each alternative would be viewed with the same speed, contributing to equal conditions during evaluation of the environment. The **weather** and **time of day** were also fixed to create equal conditions for evaluation. For every alternative it is assumed that it is a sunny day with a few clouds and every trip takes place at 10 AM. Lastly, the **orientation** of the environment is fixed, meaning that the sun is in the same place for every alternative.

3.2.3 Experimental Design Consideration and Generation

There are a number of different classes of designs to choose from when creating an experimental design. The most general class of design is the full factorial design. Hensher et al. (2015, p. 202) define this as "*a design in which all possible treatment combinations are enumerated*". For a design with six attributes and three levels each, this would mean that the total number of treatment combinations (or alternatives) would be (3^6=) 729 combinations. This number of alternatives is so large that it is not manageable to include all of the alternatives in the research. Respondents will be evaluating one alternative per experiment question. This means that they would have to answer as many questions as there are alternatives, which would become very time and energy consuming, placing an enormous burden on the respondents.

A solution for this is to use a fractional factorial design: "*designs in which we only use a fraction of the total number of treatment combinations*" (Hensher et al., 2015, p. 208). Caution has to be taken when selecting the treatment combinations for the fractional factorial design. By using a random selection of the design of the experiment it is likely to be statistically inefficient or sub-optimal. It is therefore required to use a scientific method to select the most optimal treatment combinations (Hensher et al., 2015).

This research will use an orthogonal main effects only design. Hensher et al. (2015, p.208) define orthogonality as "*a mathematical constraint requiring that all attributes be statistically independent of one another*". This allows the researcher to investigate the independent effects of each attribute. However, Hensher et al. (2015) warn that by only including main effects and ignoring interaction effects, the interaction effects will be confounded with one another and it is assumed that all interaction effects are insignificant. In practice, this may not be true. Be that as it may, including interaction effects will increase the design size, which is not favorable considering the visualization of the experiment with simulated environments.

There are software packages available to generate efficient fractional factorial designs. However, existing efficient designs are also available and can be implemented in the research. The design which will be used in this research is presented in Table 3 (Addelman, 1962). There are 18 treatment combinations in this design. A coding format has been used to represent the attribute levels, where a unique number is assigned to an attribute level. This formatting starts with 0 and goes up to L-1, with L being the number of levels for an attribute (Hensher et al., 2015). In this design every attribute has 3 levels, leading to a coding with 0, 1, and 2 to represent the levels for each attribute.

Table 3 Fractional factorial design with design coding

	A	**B**	**C**	**D**	**E**	**F**
1	0	0	0	0	0	0
2	0	1	1	2	1	1
3	0	2	2	1	2	2
4	1	0	1	1	1	2
5	1	1	2	0	2	0
6	1	2	0	2	0	1
7	2	0	2	2	1	0
8	2	1	0	1	2	1
9	2	2	1	0	0	2
10	0	0	2	1	0	1
11	0	1	0	0	1	2
12	0	2	1	2	2	0
13	1	0	0	2	2	2
14	1	1	1	1	0	0
15	1	2	2	0	1	1
16	2	0	1	0	2	1
17	2	1	2	2	0	2
18	2	2	0	1	1	0

3.2.4 Allocating Attributes

So far, the treatments combinations have been presented by coding. The next step is to assign attributes and their levels to the design codes presented in Table 3. Doing this creates interpretable treatment combinations that represent the cycling environments that will be shown to the respondents of the survey. Which attribute corresponds to which column and which level corresponds to which number is freely up to the researcher. This is convenient, for it can prevent the generation of dominant alternatives that will be overly positive or negative and the generation of extreme alternatives that are less likely to be observed in real-world environments. Be that as it may, in the creation of the levels for each attribute the idea of extreme alternatives was kept in mind, resulting in no extreme alternatives in the design. Furthermore, dominance of alternatives cannot be clearly determined beforehand, as this research aims to find out what the preferences for the attributes and their levels are. Literature in most cases does not state exact names and numbers for preference. It will merely say that for example a front garden is preferred over no garden without stating how large this garden should be. This makes it difficult to determine in advance which level will have the highest or lowest evaluation and consequently if there are dominant alternatives. Table 4 shows which attributes and levels have been assigned to which columns and design codes. In appendix B, all the 18 treatment combinations with the assigned attributes and levels can be found.

TABLE 4 ALLOCATION OF ATTRIBUTES AND LEVELS

Column	Attribute \ Design Code	0	1	2
A	Building Height	2 floors	4 floors	6 floors
B	Building Type	Historic	Modern	Mix
C	Openness of Façade	Closed façade	Semi-open façade	Open façade
D	Front Garden	No front garden	30 cm	1.2 m
E	Distance to Building	2 m	4 m	6 m
F	Activity of Ground Floor	Little traffic	Moderate traffic	Much traffic

3.2.5 Alternative Randomization

In choice situations the treatment combinations would be paired together to create choice sets that are presented to respondents. However, to reduce the burden of filling out the survey, for this research the decision was made to have participants rate environments instead of choosing between multiple environments. So only one environment will be shown per question. Therefore, there is no generation of choice sets in this research.

As mentioned earlier, the full 18 treatment combinations are shown in appendix B. The burden of filling out the survey becomes too much for the respondents if they have to evaluate all 18 treatment combinations. It was therefore decided to first show them an example question and then have them evaluate 6 alternatives. An elaborate description of the evaluation task will be given in paragraph 3.5.

An example question was added because choices made further on in the evaluation might be evaluated differently than the ones in the beginning of the evaluation due to a learning curve throughout the experiment. The example question with an explanation of the attributes and levels aims to bring respondents to the same level of understanding and gets them used to the type of questions before the actual evaluation starts. This reduces the influence of the learning curve in the data. Related to this learning curve is the issue of biases in the data due to order effects (Hensher et al., 2015). If each respondent is presented the alternatives in the same order, the alternatives in the beginning will be less reliable than the ones near the end because in the end the respondent has better learned how to interpret the attributes and how to answer the questions. To overcome this issue the order of appearance of the alternatives is randomized. By using randomization, each respondent gets 6 alternatives to evaluate, but the set of alternatives is unique for every respondent. Online survey platforms can easily perform this randomization by programming in the survey that for each survey entry 6 alternatives are to be drawn from the pool of 18 alternatives. The survey platform ensures that each alternative is added to the survey approximately the same number of times across all entries.

3.3 Presentation of the Attributes

Swelsen (2019) has looked into the types of stated preference experiments that have been conducted in various theses at the Eindhoven University of Technology at the faculty of the Built Environment over the past years. Among other aspects of stated preference experiments, she examined the options for the presentation of alternatives. Swelsen (2019) identified eight options that were used to communicate the choice alternatives or rating questions to respondents of the surveys: text only, text with preceding images and/or pictograms as explanation, text with pictograms, text with images, images only, videos, images or videos with sound fragments, and VR technology.

The simplest option would be to present the attributes by text. However, Swelsen (2019) states that by solely using text the respondent will review the choices based on their own interpretation and the interpretation of the researcher might get lost. There is also a lack of realism in the experiment as respondents have to imaging what the attributes will be like in real life. Reading a lot of text in a survey might also be time consuming and might lead to fatigue effects among the respondents. There is the option to combine text with preceding images or text to explain the attributes before respondents answer the questions. A downside of this is that respondents can forget the explanation during the experiment and return to their own interpretation. The use of pictograms is also not reviewed very positively by Swelsen (2019), as she mentions that the association with a pictogram can differ from the associated attribute. The final text option is to combine the text with images. This in general is a good option, however Swelsen (2019) found that the respondents' choice is more based on what they see than on what they read. Del Mistro & Arentze (2002) found that a visual representation of the attributes does not result in a better quality dataset. In their research a visual presentation of the attributes was compared to a verbal presentation of the attributes. Additionally, Del Mistro & Arentze (2002) concluded that a visual presentation of the attributes can add to the complexity of a choice task. This complexity can in turn lead to an increase in randomness of choice. However, based on Swelsen's (2019) evaluation of the options and the aim of the research, the main focus for the presentation of the attributes should be on the visual presentation of the attributes. The visual presentation can eventually be combined with text to further clarify the attributes.

So, a form of visual communication will be used for the presentation of the attributes in this research. Researcher and architect Arthur Stamps wrote about simulating designed environments as a visual communication method. He proposed a strategy for determining the type of visualization fitting for a research by following six steps: purpose, sensory modality, describing objects in time and space, validity, efficiency, and skills and tools (Stamps, 2016). The presentation method of the attributes is determined by following his strategy.

Purpose
The first step is to determine the purpose of the simulations: what will the simulations be used for. The simulations will be used to create environments that instantiate scientific concept. Simulations will be created within the scientific protocols of experimental design (Stamps, 2016).

Sensory Modality
Sensory modality comes down to adjusting the simulation type to senses necessary to assess the research object. Most senses are not logical to include in an experiment about the built environment, e.g. smell, taste, and touch. In most cases, the sense of vision is used to evaluate a research object. Including sound might be beneficial for some experiments, because it can increase the degree of realism of the built environment. However, it can also be a distraction from the attributes that are to be researched. It is therefore best to only include sound if it contributes to the research goal. Although this research aims to recreate a cyclist's perspective, it is focused on visual building characteristics and therefore adding senses other than vision to the experiment might only cause distraction.

Describing objects in space and time
Something that ties in closely to sensory modality is movement in the built environment. People generally use movement as a way to take in information. Stamps (2016) therefore states that if movement is required for observation, environments should be expressed dynamically rather than in static media. Because this research uses a cyclist's perspective, movement is imperative.

The selection of the viewpoint of simulations is also important for objects in space and time. When a respondent is inside an environment rather than looking at it as an object, it is a matter of empirical inquiry to determine how many viewpoints are needed. Including movement in the simulation will give multiple viewpoints of an environment compared to the singular viewpoint static images offer. The location of the viewpoints will in all simulations be at the bicycle path and at eye-level, which is on average at 175 cm.

Validity
A claim against the use of simulations is that the results obtained from simulated research do not predict responses the same way that actual environments do. It would therefore be better to use real environments over simulations. This claim has been refuted by many studies (e.g. Stamps, 2016; Van der Waerden et al., 2018; Van der Waerden & Van Kampen, 2016). Stamps (2016) conducted a research on on-site versus static media and on-site versus dynamic media that proves that there is enough correlation between on-site observations and static or dynamic media for simulations to perform adequately. Real environments might be the optimal solution for degree of realism, however, there are significant downsides to using real environments over simulations. First of all, experiments in real environments are time and money intensive. Furthermore, they are very dependent on an acceptable location. Usually there is limited availability of suitable locations which can lead to a reduction in the alternatives presented in the experiment and a higher chance of correlations between attributes (Van der Waerden et al., 2018; Van der Waerden & Van Kampen, 2016). Van Dongen & Timmermans (2019) state benefits of virtual environment in their research regarding preference for urban greenscape designs. Factors that are outside the scope of a research can be minimized so they do not interfere with the researched factors, something that cannot be

done in real world environments. Because the simulations are hypothetical locations they do not have the emotional and functional values that people connect to real world locations. The researchers mention downsides of virtual environments as well: there is a decrease in the relevance for the decision-makers, the credibility of the environment, and the legitimacy of the environments.

For the validity of simulations there are factors that require control so that the simulations are the same for all simulation sets, otherwise any conclusions drawn from the research are not valid because these differences could have influenced the respondents' decisions. These factors are location of viewpoint, camera lens, color depth, and lighting. Stamps (2016) states that when choosing a simulation type it should be considered how well the simulation type can control for these factors. By using virtual environments all these factors can be accounted for. The location of viewpoint can be at a set location for all simulations. The camera lens can be controlled by the settings of the camera in the simulation program. Color depth and lighting can be controlled by similar orientation for all simulations, adjusting the sunlight, and setting the simulation to a standard time of day.

Efficiency

Efficiency is about how much time it will take to create and render the simulations as opposed to taking pictures or videos of real world environments. The running time of the computer software for rendering should not take too long per simulation, otherwise it will be impossible to finish the research in the set timeframe. When it comes to efficiency, static simulations would be the better option because it will take less time to render an image than it does to render a video. However, dynamic simulations can still better replicate a real environment and by using the right programs it is nowadays possible to render videos rather quickly.

Skills and tools

An important aspect of simulations is the software that is used to create them. There are many different software packages available for this purpose and Stamps (2016) advises to choose the simplest format that will provide the abilities to address the purposes of the simulations. Commonly with software packages a Computer Aided Design (CAD) package is used, complemented with specialized programs for e.g. people, plants, etc.

Various programs were considered for the simulations in this research. Because the focus of this research is on aspects of buildings, each building needs specific attributes. A convenient program for the creation of buildings is Autodesk Revit (Autodesk, 2020). This is a program commonly used for BIM purposes and allows architects to quickly make 3D models of their designs. The program has pre-set elements such as doors, windows and walls that allow for simple material changes and quick construction of 3D building models. The program itself has a built-in rendering engine that allows for rendering images as well as walkthroughs (videos). However, this rendering engine takes a long time to complete the renderings at the quality levels requested for this experiment.

A solution to this is complementing Revit with the program Twinmotion (Twinmotion, 2021). The program has features such as a material library, greenery, and character paths to create moving people, bicycles, and vehicles. The time it takes to render a model is significantly less than it takes for the Revit built-in rendering engine. The program even allows to create VR environments.

Videos of simulated environments

By following the approach suggested by Stamps (2016), it was decided to create videos with simulated environments without sounds. The simulated environments that will be presented in the experiment will be modelled in Autodesk Revit and Twinmotion.

By choosing the option 'Video' there are several disadvantages that have to be overcome. First of all, there is the risk that parts of the videos will be forgotten before choosing. However, Lim, Yang, Ehrisman, Havrilesky & Reed (2020) found when comparing the use of videos to text with graphics that videos better engage survey respondents and improve the retention of the content. Swelsen (2019) does not recommend a specific visualization method in her report but focuses more on how to present a stated preference experiment to respondents in general. She does however state that for studies using VR technology an approach will best be used where the choice sets need to be rated instead of making a choice between a number of alternatives. Her reasoning can also be applied to the use of videos. Due to the high burden of watching multiple videos and then choosing an alternative, the risk occurs that part of the videos have already been forgotten. The issue of forgetting parts of the videos will be solved by accepting Swelsen's (2019) advice and not having the respondents choose between videos, but having them rate only one video per question. The option will be available to re-watch the video before rating, significantly decreasing the chance of forgetting the content of the video at hand.

Next, movement might be a distraction from the attributes that the research focuses on (Rid, Haider, Ryffel & Beardmore, 2018). However, because this research aims to create a cyclist's perspective it is imperative that movement is part of the experiment. The distraction will be diminished by minimizing the movement of objects that do not necessarily require movement for evaluation of the environment and by textually stating the attributes above the video. By stating the attributes beforehand, the respondents will know where to put their focus on.

Finally, the amount of information provided in the simulations may overstrain respondents (Rid et al., 2018). This information intake will be reduced by minimizing the implementation of factors in the simulations that are not within the scope of this research and including attributes in the experimental design that are as best as possible distinguishable from one another.

3.4 Visualization of the Attributes

Now that method of presenting the attributes and the design of the experiment are determined, the next step is to visualize the attributes and their levels. This paragraph will discuss how this is done. First, the environmental base for all simulated environments will be discussed, followed by the explanation of the modelling of the attributes.

3.4.1 Environmental Base

For the creation of the simulated environments one environmental base was used. As explained in the literature review of chapter 2, infrastructure contributes to the transportation mode choice. However, due to the focus of this research on buildings characteristics changes in the infrastructure could overrule or take away the focus from these building characteristics. Therefore, the decision was made to use a fixed layout for the environment.

The design of the environmental base is generic. It can be found anywhere in the Netherlands and is based partly on observations of routes to train stations in urban areas in the Netherlands. These observations lead to the two-way road and the measurements of the infrastructure. In the literature review, factors were found that can stimulate bicycle use. Some of these factors are incorporated in the design of the environmental base. First of all, the decision was made to use separate bicycle paths on either side of the road. Another preference that was expressed in the literature was the presence of greenery. Though the more optimal form of greenery would be trees or bushes, for research purposes it was better to only include grass. With greenery that has a larger height the issue could arise that the buildings – which are most important – could be blocked from view. A section of the environmental base can be seen in Figure 11.

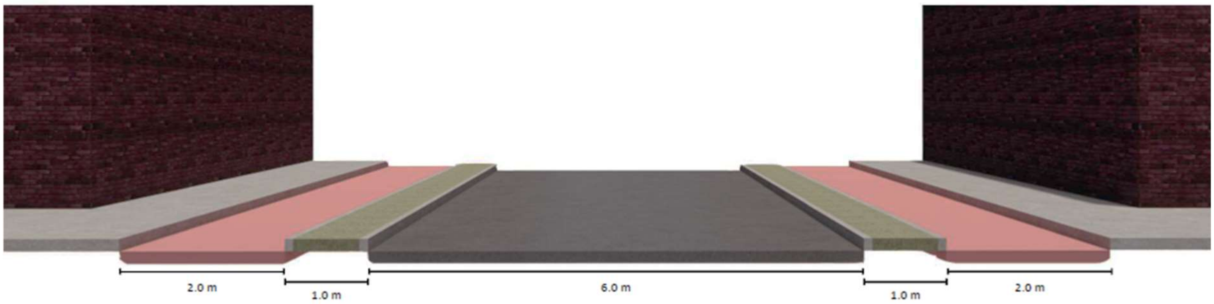

FIGURE 11 SECTION OF THE ENVIRONMENTAL BASE

3.4.2 Text to Visual

So far, the alternatives for the stated preference experiment have only been discussed textually. This paragraph will describe how the attributes and levels are made visual in simulated environments. paragraph 3.4.3 will describe the modeling choices per attribute.

To start, a distinction can be made between static and dynamic attributes. These two groups of attributes require different programs to simulate them. The largest part of the alternatives generated by the experimental design is modeled in Autodesk Revit (Autodesk, 2020). In Revit the environmental base for all alternatives and the static attributes – building height, building type, openness of the façade, front garden, and distance to the buildings – are modeled.

The current stated preference experiment only consists of one dynamic attribute: activity of the ground floor. This attribute requires moving pedestrians, cyclists, and cars to be placed in the simulated environments. To do this the program Twinmotion is used (Twinmotion, 2021). Twinmotion is an architectural visualization tool with features such as a material library, an asset library, character paths, and video options. By using character paths, continuous paths can be drawn for pedestrians, cyclists, and cars. Various settings in these character paths are possible such as speed of the character, movement direction, and density of characters. Furtermore, the material library of the program is used to change some of the materials that were modeled in Revit to increase realism and to create clearer distinctions between the buildings types. Additionally, the asset library of Twinmotion provided multiple options for plants, so these were added to the front gardens of the environments using Twinmotion. The settings that were used for the models in Twinmotion can be found in appendix C.

After adding the character paths to the model, the simulated environments are completed and videos have to be made of the alternatives to present to the survey respondents. Twinmotion additionally allows for the creation of videos of the models. A video of 15 seconds is created for every alternative from the perspective of a cyclist, with the video settings constant for every environment.

3.4.3 Attribute Modeling

The previous paragraph explained how the attributes and levels are modeled. This paragraph will look further into the choices that were made regarding visualization of the attributes and levels. Images are provided to support the textual explanation. The enlarged versions of these images can be found in appendix D.

Building Type

The decision is made to use two clearly distinguishable building types and include a mix of the two as another level. Historic buildings (left) and modern buildings (middle) are considered to be contrasting enough to be noticed while cycling. Inspiration for the design of the historic buildings is drawn from old buildings in city centers of large Dutch cities. Inspiration for the modern buildings on the other hand is drawn from newly built neighborhoods. The mixed level (right) consists of 50% historic and 50% modern buildings as not to create any bias for a building type. Figure 12 shows the modeled attribute.

FIGURE 12 MODELED BUILDING TYPE LEVELS

Building Height

The levels for this attribute are '2 floors' (left), '4 floors', and '6 floors' (right). The modeling for these levels is straight-forward. Each floor is considered to be 2.5 meters high. Figure 13 shows the height differences for the historic buildings and Figure 14 the height for the modern buildings.

FIGURE 13 MODELED BUILDING HEIGHT LEVELS – HISTORIC BUILDINGS

FIGURE 14 MODELED BUILDING HEIGHT LEVELS – MODERN BUILDINGS

Openness of Façade

The levels for the openness of the ground floor are based on observations in the Netherlands. Industrial buildings are used as a reference for the lowest levels of openness: a closed façade (left). It was not considered realistic that a building would have no windows on the ground floor, therefore this level has small windows that provide daylight on the inside but do not allow looking inside the building from the street. The semi-open façade (middle) is based on residential buildings. The windows in this level are large enough to give passers-by a glimpse of the interior of the building, but small enough that passers-by cannot see everything that goes on inside. The most open façade (right) is based on retail buildings, which have large open façades so the merchandise can be seen from the outside. The visualization of this attribute and the corresponding levels can be seen in Figure 15 and 16.

Figure 15 Modeled openness of the façade levels – historic buildings

Figure 16 Modeled openness of the façade levels – modern buildings

Distance to Buildings

For the distance from the bicycle path to the building, levels were chosen based on literature, which states that people feel enclosed by narrow streets and are more comfortable in more open spaces. Observations show that in practice fairly wide sidewalks exist. However, when making the distance too large in the simulated environments other building characteristics cannot be seen properly. The maximum level is therefore set at '6 meters' (right). A minimum of '2 meters' (left) is chosen based on observations and to leave enough room for the addition of a front garden in the simulated environments. The middle level of '4 meters' follows logically from these two end-point levels. This is modeled by placing the buildings further backwards on the environmental base, increasing the distance from the bicycle path to the buildings. This can be seen in Figure 17.

Figure 17 Modeled distance to buildings levels

Front Garden

For the first level it is determined to have no front garden (left), as this is quite common in cities, especially in city centers. The second level has a front garden as wide as a pavement tile. This is often a solution in cities to provide a bit of greenery for residents while not sacrificing much of the pavement. A common pavement tile in the Netherlands is 30x30 cm, explaining the value of 30 cm for this level (middle). The third level is considered a large garden (right). ‘Large’ is quite subjective, so to determine the value for this level other factors were taken into account. One factor was the ability to model the garden, which means for a large garden that many plants have to be placed to fill up the space and this would create a large and slow modeling file. The second factor was the attribute ‘distance’, as it had already been decided that the minimum level here would be 2 meters. To still make the pavement walkable and have a front garden a maximum of 1.2 meters could be reached for the front garden. This in practice might not be considered very large, but the size of the large front garden shows enough contrast with the small front garden for respondents to notice the difference. While in reality every front garden has different plants and designs, this is very time consuming and not manageable for the simulated environments in this research. The decision is made to make three front gardens that differ in the plants that are used. These are placed alternately in the environments to create enough variability in the garden, while reducing the modeling time significantly. The levels for the front garden can be seen in Figure 18.

FIGURE 18 MODELED FRONT GARDEN LEVELS

Activity of Ground Floor

The levels ‘little traffic’ (left) increasing to ‘much traffic’ (right) are chosen to represent the activeness of the ground floor. This was modeled by increasing the density of characters (pedestrians, cyclists, and cars) in Twinmotion. For pedestrians and cyclists ‘little traffic’ corresponds to a density of 10%, ‘moderate traffic’ to 20%, and ‘much traffic’ to 30%. Due to difficulty in the perception of difference in the density of cars with these percentages, the percentages for the cars are slightly different. For ‘little traffic’ the density of cars is 5%, for ‘moderate traffic’ 15%, and for ‘much traffic’ 30%. The velocity for the character paths for cyclists and cars are set at a fixed speed by the researcher for all levels at respectively 15 km/h and 30 km/h. The pedestrian speed is fixed by Twinmotion and can’t be altered. It is assumed that the pedestrian speed is 5 km/h. Figure 19 shows the levels visually.

FIGURE 19 MODELED ACTIVITY OF THE GROUND FLOOR LEVELS

3.5 Survey Construction

The final stage of setting up a stated preference experiment is the design and construction of the survey instrument. It is important that the chosen survey instrument is suitable for the research objective. For this research an online survey will be constructed and distributed. The instrument and design of the survey should contribute to a good understanding of the research objective, where respondents should be able to interpret the research objective as it is intended. Ambiguity in questions should be avoided. The survey instrument used in this research is the online survey platform LimeSurvey (LimeSurvey.org, 2021). This paragraph describes how the survey is structured and which questions are asked. A print-out of the full survey can be found in appendix E.

The survey starts with an introduction to the survey including a brief description of the research topic. This description is followed by the information that all results will be anonymized and will be treated confidentially. In addition, respondents are asked for their consent to collect and use their results for analysis in this research. They are guided to an informed consent form with statements about what will happen with their data. Respondents are asked to read these statements carefully and to only continue with the survey if they give their consent. The opportunity is offered to ask the researcher questions before giving consent. The handling of data collected through the survey, the consent form, and the survey in general have been approved by the Ethical Review Board of the faculty of the Built Environment at the Eindhoven University of Technology. The introduction further states the approximate time it will take to fill out the survey and notes that it is advised to take the survey on a pc or tablet. To make the survey accessible for as many people as possible, there is also the option to change the survey language from Dutch to English.

The survey consists of five parts. The first three parts are respectively about the respondent's current travel behavior, their cycling route to the train station, and the importance of certain factors in their decision to cycle. The fourth part is the stated preference experiment. The survey ends with questions about the respondent's personal information to be able to test the representation of the sample and to identify sub-groups within the sample.

In the first part of the survey respondents are asked about their current travel behavior. This part includes questions about cycling frequency in general and to the train station specifically, cycling distance, most used bicycle type, and frequency and purpose of train travel. Furthermore, it is asked if the respondent has any impediments that can influence their cycling experience, and, if they indicate never to cycle, what is holding them back from cycling. Conditions are set to the survey to prevent inconsistency in the respondent's answers. If a person indicates that they never cycle, the cycling questions are filtered out. Same goes for the train questions. All these questions are added to place the results in the right context. With these results it might also be possible to identify sub-groups in the sample.

The second part of the survey is about the cycling route to the train station. In this part the respondents are asked what the travel distance is from home to the train station, in order to be able to later determine if the degree of stimulation of building characteristic on the route are different for people living close to the train station as opposed to people living far away. Furthermore, statements are added regarding the environmental characteristics on their route. These characteristics are based on the attributes that are researched in the stated preference experiment. This question serves to make the respondents familiar with the attributes before the experiment starts.

The third part of the survey contains statements to determine how important certain factors are for a respondent in their decision to cycle in general. The purpose of these statements was to investigate how important the surroundings while cycling are compared to the other factors.

The fourth part of the survey is the stated preference experiment. This part starts with a short introduction of the experiment and the attributes. In the introduction the respondents are informed that per question they are going to watch a 15-second video showing a virtual environment from the perspective of a cyclist. It is explained that characteristics of the environment will change in the videos. Immediately afterwards it is stated which characteristics will change. The questions that will be asked for each situation are also presented in the introduction. Respondents are asked to evaluate the shown environment on the following four aspects on a five-point scale ranging from '- -' (to a very limited extent) to '++' (to a very large extent):

- The degree to which the environment stimulates them to cycle in general;
- The degree to which the environment stimulates them to cycle to the train station;
- The attractiveness of the environment (how pleasant the respondent finds the environment to cycle in);
- The bicycle-suitability of the environment (how suitable the respondent finds the environment for cycling).

It is also pointed out to the respondents that for the best experience it is highly recommended to watch the videos in full screen.

After the introduction an example situation is shown with a simulated environment that is not part of the experimental design and further analyses. The attributes and their levels are stated above the video to inform the respondents what the relevant characteristics in the video are.

Next, the experiment itself begins. For each respondent 6 virtual environments (alternatives) are randomly selected from the set of 18 environments to evaluate. The respondent is invited to watch the video and answer the four questions on a scale from '- -' to '++'. An example of this part of the survey can be seen in Figure 20.

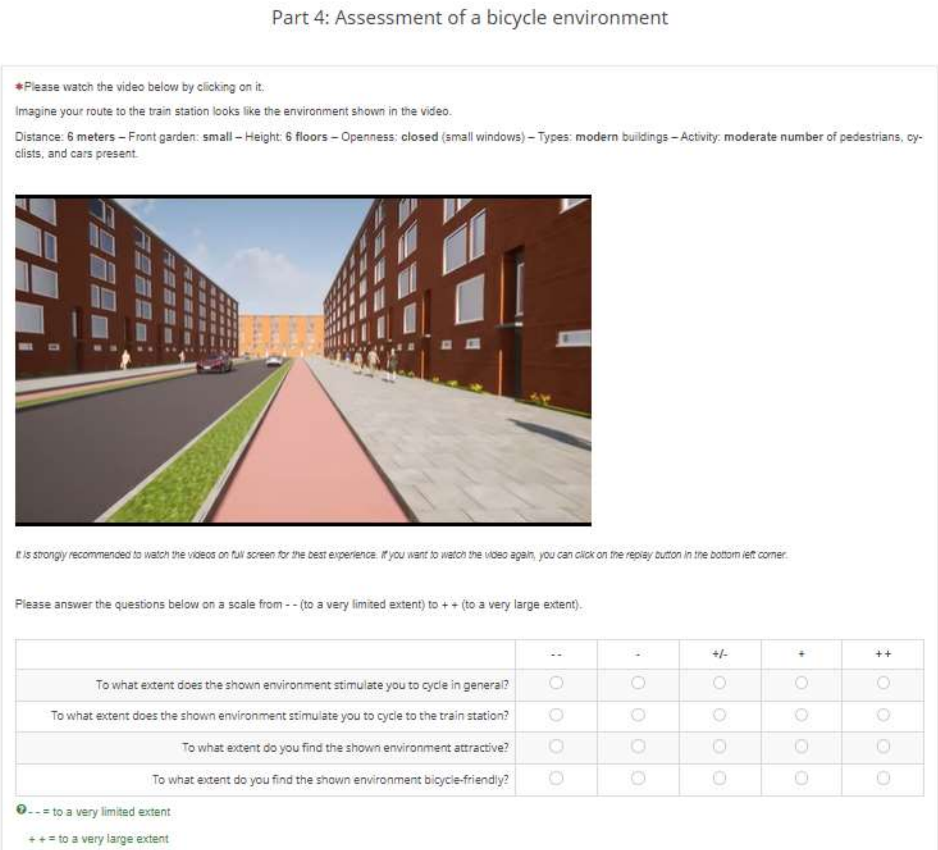

FIGURE 20 STATED PREFERENCE EXPERIMENT IN THE SURVEY

The last part of the survey is focused on collecting personal information from the respondents. Questions are asked regarding gender, age, education, household composition, and postal code. These questions make it possible to check the representativeness of the sample and to possibly divide the sample into sub-groups. After filling out these questions, the respondents get the option to leave any questions or comments regarding the survey or the research. The survey concludes with a message thanking the respondent for participation. In Table 5 an overview can be seen of all the variables in the survey.

TABLE 5 OVERVIEW OF SURVEY

Parts	Variables
1: Current Travel Behavior	Cycling frequency in general
	Average cycling distance
	Bicycle type
	Impediments for cycling experience
	Frequency train travel
	Purpose train travel
	Cycling frequency to train station
	Reason for never cycling to train station
2: Cycling Route to Train Station	Travel distance from home to train station
	Environment characteristics on route
3: Decision Factors for Cycling	Importance of factors in the decision to cycle
4: Stated Preference Experiment	Stimulation of the environment to cycle in general
	Stimulation of the environment to cycle to train station
	Attractiveness of the environment
	Bicycle-suitability of the environment
5: Personal Information	Gender
	Age
	Education
	Household Composition
	Postal code

3.6 Data Collection and Processing

With the survey now constructed the data collection can start. It is difficult to say how many responses are necessary for significant results. Hensher et al. (2015) mention that little is known about the sample size requirements for models estimated from stated preference data. The equation proposed by Orme (2010) can be used to make an estimation of the minimally required sample size. With 6 tasks per respondent (t), 1 alternative per task (a), and 3 being the largest number of levels for any of the attributes (c), calculating the sample size (N) would mean that a minimum of 250 respondents (1500 observations) is required for significant results.

$$N \geq 500 \cdot \frac{c}{t \cdot a} \tag{5}$$

The survey is distributed online through a panel called 'Zuid-Limburg Bereikbaar' that is focused on mobility in the south of the Netherlands. Once the data is collected through the online survey, the processing of the data set can start. All unfinished surveys are excluded from the data set. That was the only criterium to exclude responses, as furthermore completion times of the survey were examined, but none were found to be overly unrealistic, and inconsistent answers regarding current travel behavior were not possible due to the constraints set in the survey. Further, the data set was prepared for analysis by effect coding the preference data. After preparing the data set, the next step is to perform the analyses.

3.7 Models for Analysis

Paragraph 3.7.1 explains the models that will be used for the analyses of the preference data collected through the survey. Consequently, paragraph 3.7.2 describes the equations that can be used to determine the model fit of the estimated models.

3.7.1 Model Explanation

There are various models that can be estimated for preference data, of which five will be discussed in this paragraph and will eventually be used for analysis of the data. It concerns the Ordered Logit model, the Random Effects model, the Latent Class model, the Multinomial Logistic Regression model, and the Linear Regression model.

3.7.1.1 Ordered Logit Model

First, there is the Ordered Logit Model. This model was developed for the analysis of categorical data of ordinal measurement levels. According to Kemperman (2000) the Ordered Logit Model is traditionally applied in applications such as surveys, in which respondents express a preference in terms of ordinal ranking. This is the first model that will be estimated in the analyses of the dependent variables, as these variables have ordinal scales for the rating of the alternatives. The foundation of the model is an underlying utility function:

$$y_i^* = \beta' x_i + \varepsilon_i \tag{6}$$

In the function β expresses the part-worth utilities, the variables (i.e. attributes) x_i, and a random error component ε_i. In an Ordered Logit model it is assumed that the error component has a standard logistic distribution instead of a normal distribution as is the case for the Ordered Probit model. The continuous latent utility y_i^*, is observed in discrete form through a censoring mechanism:

$$\begin{aligned} y_i &= 0 \; if \; \mu_{-1} < y_i^* < \mu_0 \\ &= 1 \; if \; \mu_0 < y_i^* < \mu_1 \\ &= 2 \; if \; \mu_1 < y_i^* < \mu_2 \\ &= \cdots \\ &= J \; if \; \mu_{J-1} < y_i^* < \mu_J \end{aligned} \tag{7}$$

Equation 6 takes into account the observed discrete choice of the respondent, $y_i = 0,1,\dots,J$. Furthermore, the model contains threshold parameters μ_j that are estimated using a sample of *n* observations, which are indexed by *i*=1,…,n. The probability function is described by equation 7:

$$P(y_i = j|x_i) \quad = P(\varepsilon_i < \mu_j - \beta'^{x_i}) - P(\mu_{j-1} - \beta' x_i), j = 0,1, \dots, J \tag{8}$$

According to Hensher et al. (2015) several normalizations are necessary to identify the model parameters. First of all, because of the continuity assumption, it is required for $\mu_j > \mu_{j-1}$. Second, to be able to use the entire real line $\mu_{-1} = -\infty$ and $\mu_J = \infty$. Lastly, it is require that $\mu_0 = 0$. By adding an overall constant to the function, only J-1 threshold parameters are needed to divide the real line in J+1 intervals.

3.7.1.2 Random Effects Model

The Random Effects model used for this research is similar to the Ordered Logit model. However, the Ordered Logit model assumes fixed effects, whereas the Random Effects Model does not estimate one true effect, but estimates the mean of a distribution of effects based on the assumption that the true effect size varies (Borenstein, Hedges, Higgins & Rothstein, 2009). The Random Effects model takes heterogeneity into account by including the standard deviation σ. According to Hensher et al. (2015, p. 813) in the Random Effects model only the constant is random. Combining the constant with the standard deviation would mean that the constant that is calculated varies for every individual. Consequently, the probability that individual *q* will choose alternative *i*, given choice-set A_q, is dependent on the value of the constant for that individual. This model will only be used to investigate heterogeneity in the preference data. However, because the Random Effects model does not provide information on underlying groups and the results cannot be linked to underlying personal and background characteristics, the model will not be discussed in further detail.

3.7.1.3 Latent Class Model

Although the Random Effects model takes into account heterogeneity, it only applies to the constant. However, the values of the estimates can also be influenced by heterogeneity. A model that implements heterogeneity is the Latent Class model (Hensher et al., 2015). The theory behind the Latent Class model states that individual behavior depends on observable attributes and on latent heterogeneity that can vary based on unobserved factors. The model assumes that individuals can be sorted into a finite number of clusters of individuals with similar preferences. The clusters based on differences in preference are called the latent classes. The Latent Class model determines the estimates for each class $\beta_{k,c}$ and calculates the probability of class membership for every individual. The researcher can then assign a class to an individual based on the highest probability. Once classes are assigned to individuals further research can be executed to examine if there are personal characteristics that are related to the choice behavior of the classes (Hensher et al., 2015). Equation 8 displays the probability *P* that individual *q* chooses alternative *i*, given choice-set A_q, and given that they are a member of class *c*.

$$P(i|A_q, c) = \frac{exp \sum_k \beta_{k,c} x_{k,i}}{\sum_i exp \sum_k \beta_{k,c} x_{k,i}} \quad i \in A_q \tag{9}$$

3.7.1.4 Multinomial Logistic Regression Model

The Multinomial Logistic Regression (MLR) model can be named the most commonly used model for the analysis of preference data. As opposed to the Ordered Logit model, this model does not consider the ordinal structure of a dependent variable, but instead regards the choice options as nominal (meaning that there is no set order in the choice options). In this research this model will be used when the preference data for a variable does not meet the requirements that allow an Ordered Logistic Regression and to investigate if there are personal characteristics that underly the classes identified in the Latent Class model.

The model assumes that random variables (unobserved effects) are independently and identically distributed. Hensher et al. (2015) explain this further by stating that 'independent' means that there are zero covariances or correlations between the unobserved effects, and 'identical' means that the distributions of the unobserved effects are all the same. The model determines the relationship between the given choice options and the alternative specific attributes. The probability that alternative *i* is chosen, given choice-set A_q, is explained by equation 9:

$$P(i|A_q) = \frac{\exp(V_i)}{\sum_{i'} \exp(V_{i'})} \quad i, i' \in A_q \tag{10}$$

The observed utility V_i is used in the probability calculation. In equation 3 it is explained that this utility can be calculated with the observed attribute variables and the parameter estimates.

3.7.1.5 Linear Regression Model

A Linear Regression model predicts the dependent variable y based on one or multiple independent variables x and describes the dependent variable with a straight line – i.e. it describes a *linear* relation. A linear regression that only has one independent variable is called a simple linear regression. However, in this research multiple independent variables are included, which requires a multiple linear regression (Field, 2009). In the linear regression the dependent variable has a continuous scale, as opposed to the ordinal scale used for the Ordered Logit model. For dependent variables with an ordinal scale it is difficult to combine the variables for analysis. Therefore, the ordinal scale of the dependent variables is transposed to a continuous scale for the analyses of combined dependent variables. The equation for the Linear Regression model is shown in equation 10:

$$y = \beta_0 + \sum (\beta_n x_n) + \varepsilon \tag{11}$$

In this equation β_0 is the constant generated by the model and β_n is the regression coefficient for independent variable x_n. An error term is added that describes the difference between the predicted and the observed value of the dependent variable y (Field, 2009).

3.7.2 Determination of Model Performance

To determine the performance of the estimated models, a Maximum Likelihood Estimation (MLE) can be used. Given the observed chosen alternatives in a dataset, the likelihood function estimates the probability that alternative *i* will be chosen. The likelihood function is designed in such a way that it maximizes the predications made by the model. The log likelihood of the estimated model $LL(\beta)$ is calculated with the probability that individual q will choose alternative *i* (p_{iq}) and the actual choice (y_{iq}) which has a value of 1 if alternative *i* is chosen by individual q and otherwise a value of 0. With the MLE the product of a series of probabilities is calculated, which often results in extremely small values that cause rounding errors in most software, and consequently less accurate results. It is therefore more common to maximize the log of the likelihood function, which achieves its maximum value at the same points as the function itself (Hensher et al., 2015). The formula for calculating the log likelihood of the estimated model is given in equation 11.

$$LL(\beta) = \sum_{q} \sum_{i} y_{iq} \cdot \ln{(p_{iq})} \tag{12}$$

The log likelihood of the estimated model is compared to the log likelihood of the null model to determine if the estimated model is better at predicting the choices. The formula for the log likelihood of the null model can be derived from equation 11. In the null model no parameters are included, which means that the probability that individual q will choose alternative i (p_{iq}) is the same for all choice options and is equal to 1 divided by the number of choice options x. This is shown in equation 12. The model with the highest log likelihood is the best predictor (Hensher et al., 2015).

$$LL(0) = \sum_{q} \sum_{i} y_{iq} \cdot \ln{(\frac{1}{x})} \tag{13}$$

With the likelihood values the performance of the models and the goodness-of-fit can be calculated. A method to determine if an estimated model outperforms the null model is the Likelihood Ratio Statistic (LRS) (Hensher et al., 2015). The LRS can be calculated with the log likelihood of the null model ($LL(0)$) and the estimated model ($LL(\beta)$) using equation 13.

$$\begin{gathered} LRS = -2(LL(0) - LL(\beta)) \\ \sim\chi^2_{(number\ of\ parameters\ in\ LL(\beta) - number\ of\ parameters\ in\ LL(0))} \end{gathered} \tag{14}$$

The calculated LRS is then compared to a Chi-square statistic for *n* degrees of freedom, where n is equal to the number of parameters in the estimated model minus the number of parameters in the null model. In Chi-square tables the corresponding value for n degrees of freedom at a confidence interval of 95% can be found. The calculated LRS has to be higher than the Chi-square statistic for *n* degrees of freedom to reject the null hypothesis that the estimated model does not outperform the null model. In other words, if the calculated LRS has a higher value than the critical (or test) Chi-square, the estimated model performs better than the null model.

The goodness-of-fit of a linear regression model, how well the data fits the model, can be determined by calculating the R^2 statistic. The goodness-of-fit of a preference model can be determined by calculating McFadden's Pseudo R^2 statistic. With the estimated model and the null model the Pseudo R^2 can be calculated:

$$R^2_{pseudo} = 1 - \frac{LL(\beta)}{LL(0)} \tag{15}$$

The R^2 for preference models is not analogous to the R^2 for a linear regression model, because a linear regression model is linear, whereas a preference model is non-linear (Hensher et al., 2015). Hensher et al. (2015) provide a graph (Figure 21) that allows comparison of the linear R^2 with the pseudo-R^2. This graph shows that a pseudo-R^2 of approximately 0.3 offers a decent model fit, as this is equivalent to a linear R^2 of approximately 0.6.

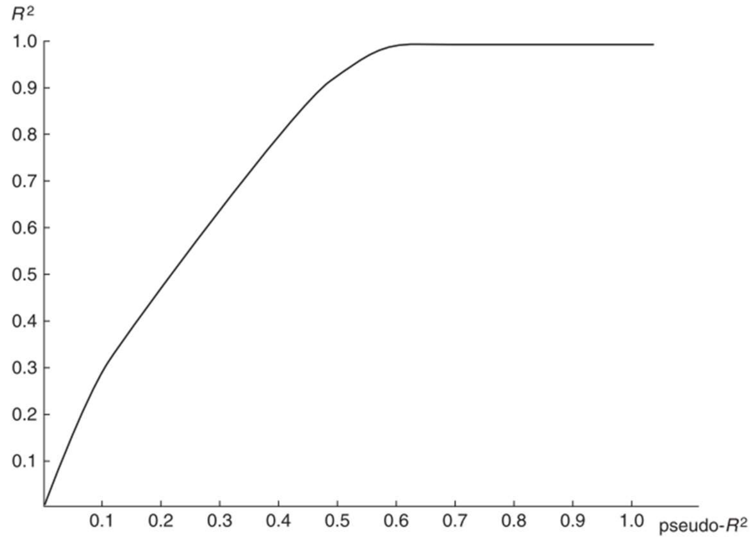

FIGURE 21 LINEAR R^2 MAPPED TO THE PSEUDO-R^2 (HENSHER, ROSE & GREEN, 2015)

To compare models, the Akaike Information Criterion (AIC) can be used, which is given in equation 15. The AIC estimates the quality of statistical models by taking into account the log likelihood of the estimated model and the number of estimated parameters *k*. With the AIC the likelihood that a model successfully predicts upcoming values is estimated (Akaike, 1974). When models are compared, the model with the lowest AIC value can be considered the best model. The AIC can also be converted to a ratio value by dividing the AIC by the number of observations *N* in the model. This is shown in equation 16.

$$AIC = -2(LL(\beta) - k) \tag{16}$$

$$AIC_{ratio} = \frac{-2(LL(\beta) - k)}{N} \tag{17}$$

3.8 Conclusion Methodology

This chapter explained the methodological approach of the research, the setup of the experiment, and the construction of the survey. After considering the available options to measure preferences, it was decided to use a stated preference experiment with a rating task where the attributes are presented by short videos of simulated environments, accompanied by a short text with the levels of the attributes to lay the focus on the right elements in the videos. The aim of the research is to gain insights in people's preferences regarding building characteristics along a cycle route to the train station that could stimulate them to cycle.

Additionally, the evaluations of certain building characteristics are examined for cycling in general to be able to compare it with cycling towards stations. Furthermore, to answer one of the sub questions of the research, respondents are also asked to evaluate the simulated environments on attractiveness and bicycle-suitability.

The constructed online survey is implemented in LimeSurvey and consists of five parts. In the first three parts questions are asked about respondents' current travel behavior, experience with traveling by bicycle and train, and the characteristics of their route to the train station. Additionally, respondents are asked to rate the importance of certain factors in their decision to cycle. The fourth part of the survey is the Stated Preference experiment. Respondents evaluate six randomly selected alternatives on how much the environment stimulates them to cycle in general, cycle to the train station, on attractiveness, and on bicycle-suitability. The evaluations are executed on an ordinal five-point scale ranging from '- -' to '++', which makes it possible to use an Ordered Logit model for the analyses. The other models discussed in paragraph 3.7.1 are used for further in-depth analysis. The last part of the survey collects details about the respondents' personal characteristics.

4. Results

This chapter presents the results of the conducted analyses. The software that is used to execute the analyses are IBM SPSS Statistics 27 and NLOGIT 6. In paragraph 4.1 a descriptive analysis is performed to determine the representativeness of the respondents for the Dutch population. In paragraph 4.2 the stated preference data is analyzed for the variables ‘Cycling in General’ and ‘Cycling to the Train Station’. The difference between these variables is examined along with the significance and strength of the attributes in determining how much the selected building characteristics can stimulate bicycle use. In paragraph 4.3 the stated preference data for the variables ‘Attractiveness’ and ‘Bicycle-Suitability’ is analyzed. Same as for the ‘Cycling’-variables, the difference between the variables and the significance and strength of the attributes are examined. At the end of the chapter, the results are compared to the reviewed literature and discussed.

4.1 Descriptive Analysis

The survey was distributed online among members of the ‘Zuid-Limburg Bereikbaar’-panel. At the time of distribution the panel consisted of 4236 members. The data collection began on 16 August 2021 and was completed on 31 August 2021. During this time the survey was started by 1143 respondents. Of the respondents who started, 894 respondents finished the survey, giving the survey a completion rate of 78%. The unfinished survey responses were not useful for the analyses because they were either missing the stated preference experiment or the personal information necessary to place responses in the right context and to identify groups within the experiment results. The unfinished survey responses are therefore excluded from the final dataset.

Background characteristics of respondents were collected in the survey. These characteristics provide context for the survey data. By identifying the characteristics of the respondents, the sample can be compared to the general population and the data can be analyzed in further detail (for example to investigate if certain characteristics are related to certain results). Descriptive analysis is used to analyze the data on characteristics and describe the sample.

4.1.1 Respondents’ Characteristics

One part of the survey contained questions about the respondents’ personal characteristics. The descriptive statistics regarding these characteristics will be presented in this paragraph to give insights in the composition of the sample. The respondents’ characteristics will be compared to the characteristics of the general population of the Netherlands to check the representativeness of the sample. The data of the Dutch population that is used for comparison is retrieved from the Central Bureau of Statistics (CBS).

Gender

Figure 22 shows the gender ratio from both the sample and the Dutch population. It appears that the ratios are exactly the same. This indicates that regarding gender the sample is representative for the Dutch population.

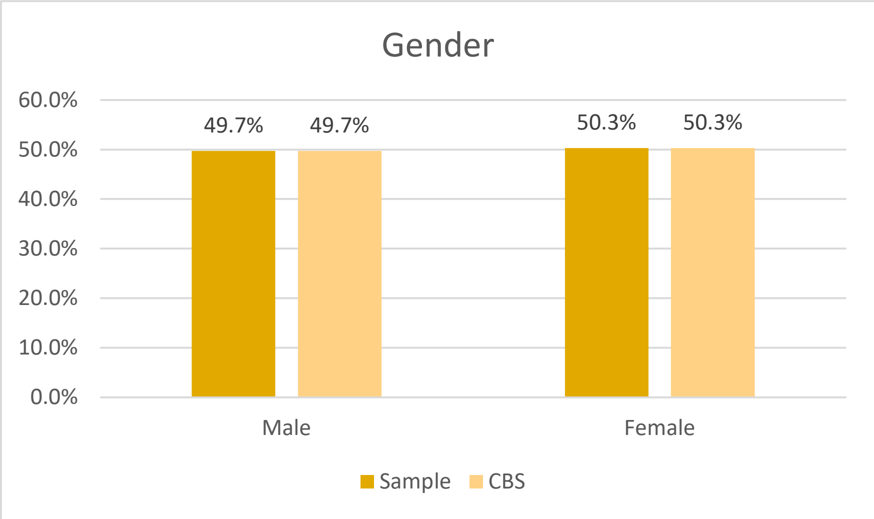

Figure 22 Gender ratio (n=894)

Age

In Figure 23 the age distribution can be seen. There is a very large under-representation of the 'Younger than 20 years'-group. This could be explained by the target audience of 'Zuid-Limburg Bereikbaar', which consists mainly of commuters (Zuid-Limburg Bereikbaar, 2021). The '20-29 years'-group is also under-represented. The '30-39 years'-group is slightly under-represented, but this is a minimal difference. The '40-49 years'-group is somewhat over-represented. The groups '50-59 years' and '60-69 years' are rather over-represented, both of them being more than twice as large in the sample compared to the general population. A possible explanation for this is that the majority of panel members of 'Zuid-Limburg Bereikbaar' are within these age categories. Since the panel was the only respondent group approached to fill in the survey this will lead to an over-representation of these groups in the sample. These results are in line with the results of Burger (2021), who used the same panel in his research. Though his age groups are categorized slightly different, there is an over-representation for ages between 40 and 65 years. Lastly, the '70 years or older'-group is under-represented.

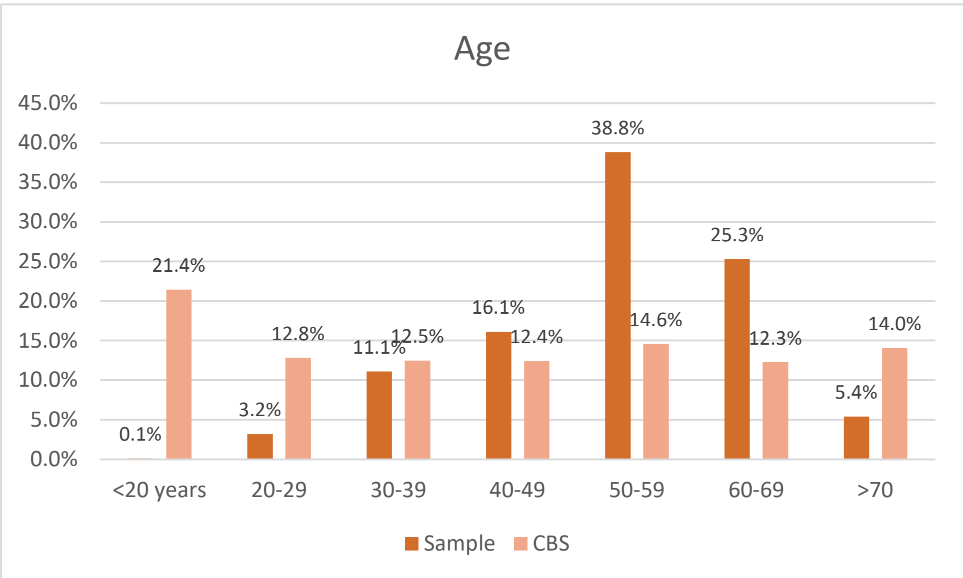

Figure 23 Age ratio (n=894)

Education Level

The distribution of the education level is also not representative for the Dutch population, as can be seen in Figure 24. The people who have only had primary or secondary general education are quite under-represented. The group of people with higher education, on the other hand, is rather over-represented. The graph is clearly skewed towards the higher education level. A possible explanation for this over-representation could be that through the online distribution of the survey a part of the Dutch population is reached that has a job that requires the use of a computer. These type of jobs are often related to higher education levels, whereas lower education levels are often linked to manual labor.

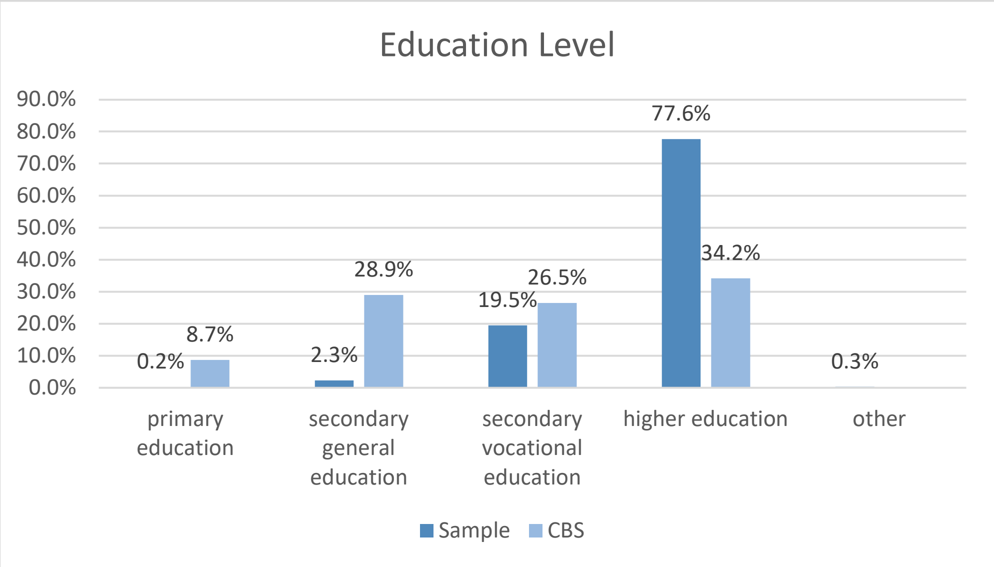

FIGURE 24 EDUCATION LEVEL RATIO (N=894)

Household Composition

Figure 25 shows the distribution of the respondents' household composition. The people who live at home with their parents are very under-represented. This can be explained by the age distribution and composition of the panel discussed earlier. The group of people that live at home with their parents are commonly people under approximately the age of 20 years. The

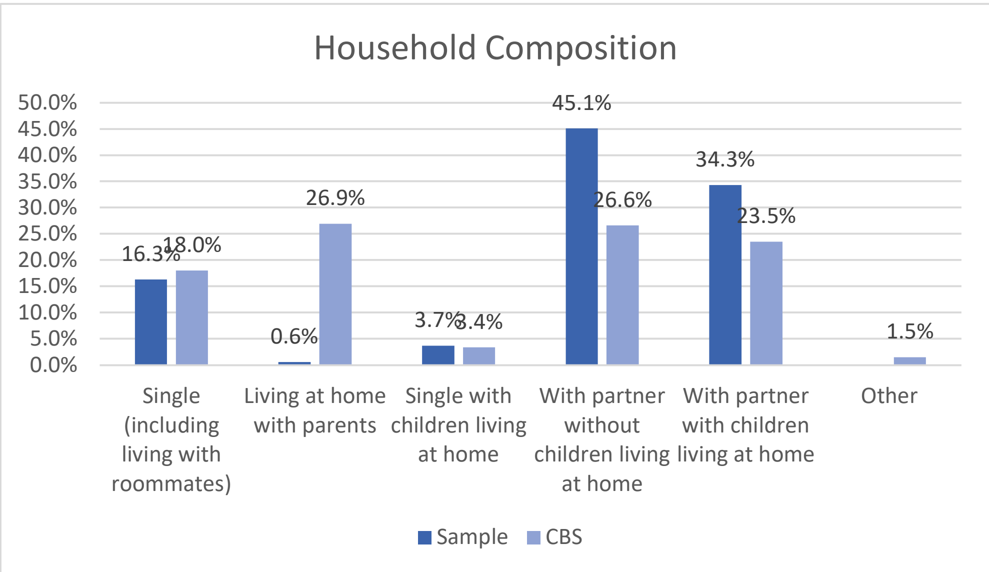

FIGURE 25 HOUSEHOLD COMPOSITION RATIO (N=894)

representation of people aged under 20 years is very low. The age distribution also explains the over-representation of the households 'with partner'. There is an over-representation of people aged 40 to 69, which are usually the people who live with a partner (either with or without children living at home).

Urbanity Level
In Figure 26 the level of urbanity of the regions in which the respondents live is displayed, compared to the level of urbanity in which the general Dutch population lives. Overall, the sample shows a good representation of the Dutch population. Only the 'Very Highly Urban'-group is under-represented. The group 'Not Urban' is over-represented. This can be explained by the region in which the survey was distributed: the south of Limburg. Though in Limburg many people live in the vicinity of urban areas, they live in non-urban areas.

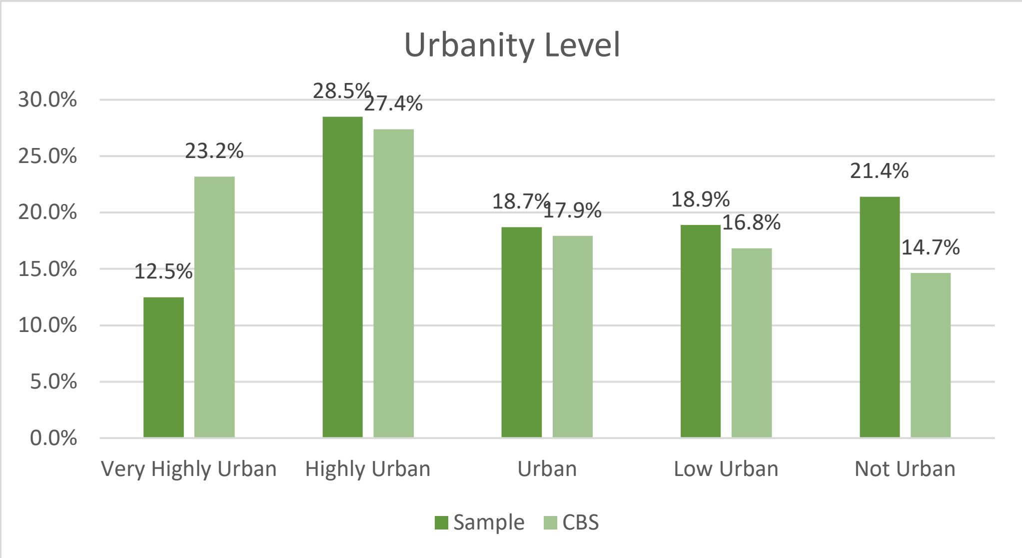

FIGURE 26 URBANITY LEVEL RATIO (N=894)

Conclusion of Respondents' Characteristics
Regarding the representativeness of the sample it can be concluded that the sample is not representative for the Dutch population. Whereas the distribution of 'Gender' and 'Urbanity Level' is good, the distribution of 'Age', 'Education Level', and 'Household Composition' is not in line with the general Dutch population. A better representation of the Dutch population in the sample would make the results generalizable for the entire Dutch population.

4.1.2 Respondents' Experience with Traveling by Bicycle and Train

The first part of the survey covered questions regarding the respondents' current travel behavior, with a focus on the bicycle and train. The questions asked are among other things directed at frequency of travel, travel distance, and bicycle type. When respondents answered 'never' to either a cycling or train frequency question, other respectively cycling and train questions were considered as 'not applicable' and were not shown to these respondents.

With regard to the cycling frequency, more than half of the respondents cycle often or very often. These high numbers indicate that the sample is quite experienced when it comes to cycling. Only a small portion of the respondents say that they never cycle. These people were not shown follow-up questions regarding cycling.

Regarding average cycling distance per week, approximately 50% of the respondents cycle 20 km or less per week, followed by a quarter of the respondents cycling between 21 km and 50 km. The expectation was that most responses would fall within these groups based on the average cycling distance in the Netherlands. The average cycling distance per person per day is 2.61 km (Central Bureau of Statistics, 2021), which corresponds to 18.27 km per person per week. This is quite in line with the distances provided by the respondents, as can be seen in Figure 27. It can be concluded that the majority of the sample is experienced in short distance travel by bicycle. Only a small portion of the sample (24.0%) cycles longer distances per week.

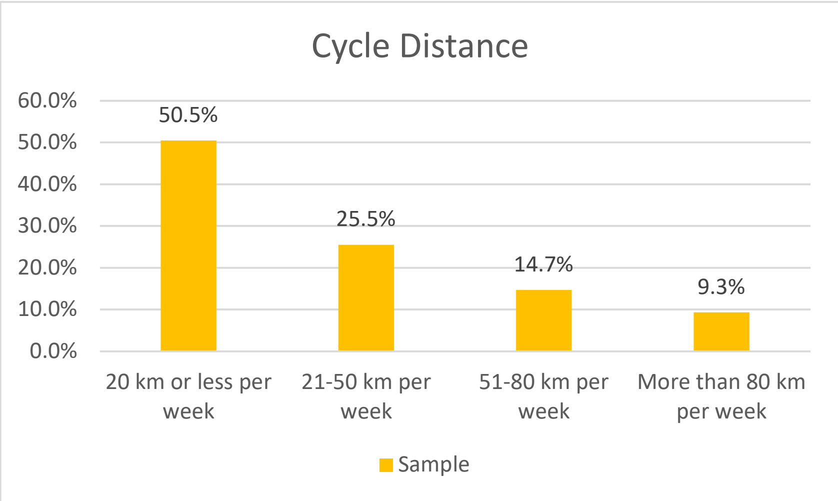

FIGURE 27 AVERAGE CYCLE DISTANCE PER WEEK RATIO (N=836)

In the most recent data from the CBS about the mobility of individuals per transportation mode no distinction is made between the standard bicycle and the e-bike. KiM Netherlands Institute for Transport Policy Analysis, however, states that in 2019 18% of all bicycle displacements were made using an e-bike (KiM Netherlands Institute for Transport Policy Analysis, 2020). This data is used to compare with the sample, even though no further specification is made in the bicycle types. Every displacement that was not done by e-bike is considered in this comparison as a displacement using a standard bicycle due to lack of more specific data. In the survey it was possible to answer 'other'. Only a small percentage indicated to use another type of bicycle than the standard bicycle or e-bike. Most often mentioned were the race bicycle and mountain bike, but these individual counts were too small to create

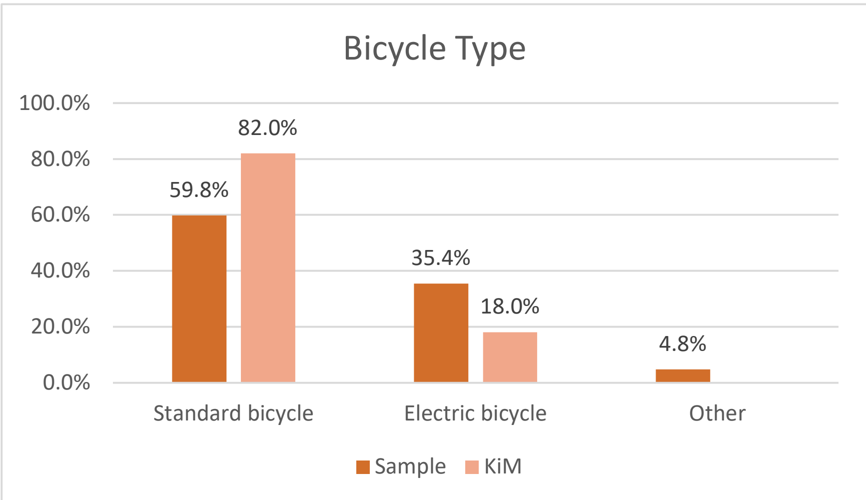

FIGURE 28 BICYCLE TYPE RATIO (N=836)

separate categories. The graph in Figure 28 shows that there is an under-representation of standard bicycle use and an over-representation of electric bicycle use.

The frequency of train travel among the respondents can be seen in Figure 29. The graph clearly shows that most of the respondents do not regularly travel by train. More than 50% say that they travel less than once a month by train, and approximately one third of the sample say that they never travel by train. According to the CBS (2021) the average displacement by train per person per day is 0.03. This is only 0.21 displacements per week, 0.84 displacements per month. The sample is in line with these CBS numbers, as the largest group travels less than once a month per train.

When asking what the purpose of the trip is when traveling by train, the majority of the respondents answered that the purpose is ‘work’ (nearly 50%), which would not be expected when most respondents travel less than once a month by train. It should be noted that this survey was conducted during the COVID-19 pandemic, where many people are working from home. It is possible that the train travel frequency of the lower scoring groups is higher when there is no pandemic. This hypothesis is supported by the CBS numbers of 2018 and 2019, where the average displacement by train was for both years 0.08 per person per day (2.24 per person per month) (Central Bureau of Statistics, 2021).

Other travel purposes the respondents answered were travel for recreation (27.1%), visiting friends and family (17.5%), shopping (5.2%), and other purposes (3.1%).

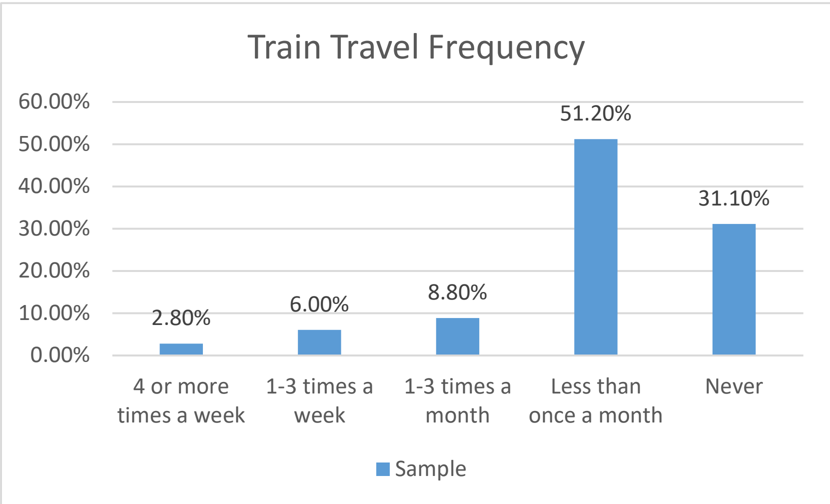

FIGURE 29 TRAIN TRAVEL FREQUENCY RATIO (N=894)

The people who previously stated to cycle and to travel by train were asked how often they cycle to the train station. Almost 50% answered that they cycle less than once a month to the train station. About 30% said they never cycle to the train station. The KiM states that approximately 43% of the train travelers use the bicycle as pre-transport (KiM Netherlands Institute for Transport Policy Analysis, 2020). A high proportion of the sample does not cycle very often to the train station and that is not in line with the numbers published by the KiM.

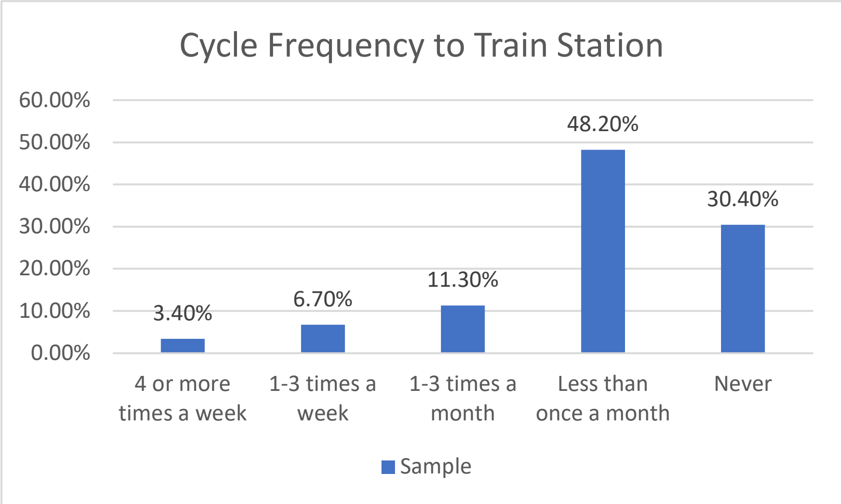

FIGURE 30 CYCLE FREQUENCY TO THE TRAIN STATION RATIO (N=583)

In the survey it was also asked if the respondents had any reasons (e.g. visual or physical disability) that could affect their cycling experience, of which the majority (89.6%) said that they do not. Furthermore, the question was asked, if respondents stated that they never cycle to the train station, what is holding them back from cycling. More than half of the respondents (50.3%) indicated that distance is the most determining factor in this. Either respondents say they live too far away from or too close to the train station to cycle. Other reasons that were mentioned multiple times were safety related (8.5%) (e.g. fear of getting their bicycle stolen at the station), and lack of cycling facilities (6.8%).

4.1.3 Route Characteristics

Another part of the survey looked into the respondents' route characteristics from their home to the nearest train station. This was with the purpose of familiarizing the respondents with the attributes that are included in the stated preference experiment part of the survey. Figure 31 shows to what extent the respondents agree with the statements about their route characteristics. From the graph it can be concluded that the majority of the sample is more familiar with low-rise buildings, much variety in the buildings on the route, open façades, quite some greenery, few pedestrians, and many cyclists and cars.

Furthermore, respondents were asked about the travel distance from their home to the train station. More than 60% of the respondents have to travel less than 5 km to the train station, and more than 25% between 5 km and 10 km.

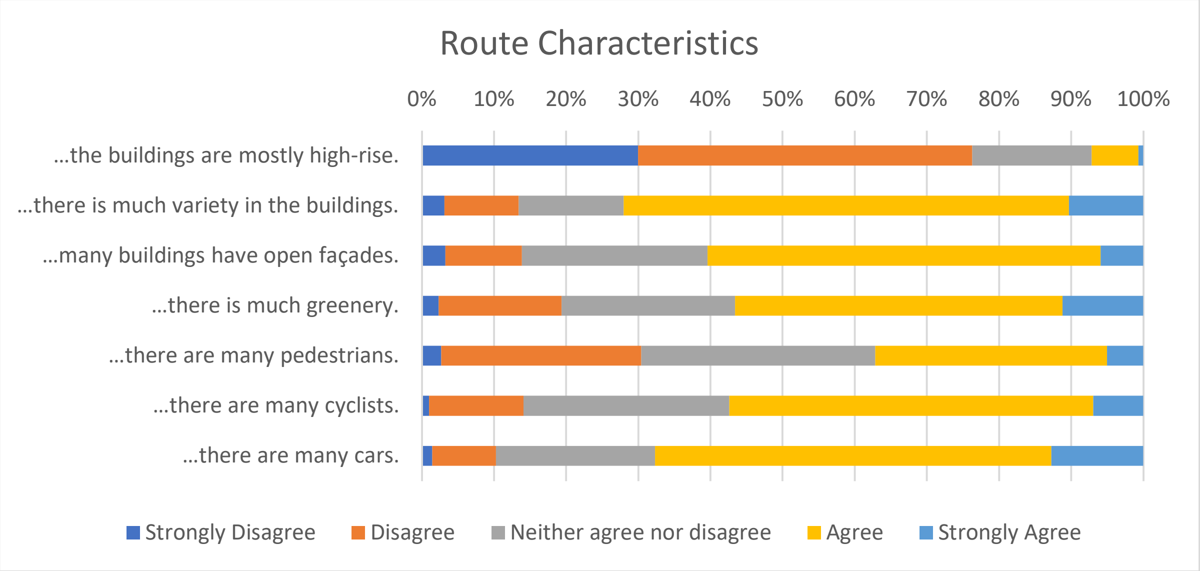

FIGURE 31 ROUTE CHARACTERISTICS OF THE RESPONDENTS ROUTE TO THE TRAIN STATION (N=894)

4.1.4 Importance of Factors on Decision to Cycle

In a different part of the survey respondents were asked to indicate how important certain aspects are in their decision to cycle. In Figure 32 these factors can be found. This section was included in the survey to see how surroundings score as a factor in the decision to cycle compared to other factors. The ranking of 'surroundings' among these factors helped create an expectation for the results of the analyses of the preference data. The expectation was that if it scored low on the ranking not many, or even none, of the building characteristics would be significant and building characteristics would not or to a limited extent contribute to the willingness to cycle. If it scored high, it was expected that building characteristics would greatly contribute to the willingness to cycle. However, 'surroundings' scored in the middle of the ranking, which led to the expectation that at least a few building characteristics will contribute to the willingness to cycle but might not contribute to a large extent.

Among the respondents, 'health' was seen as the most important factor in the decision to cycle, whereas money was deemed least important.

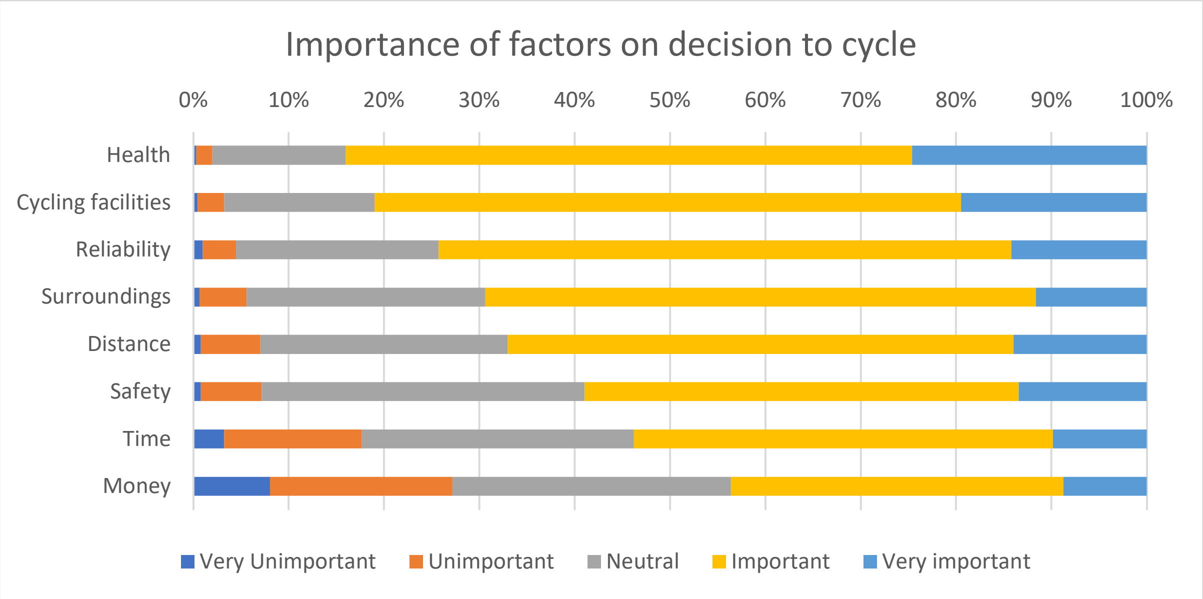

FIGURE 32 IMPORTANCE OF FACTORS ON DECISION TO CYCLE (N=894)

4.2 Model Estimation Stimulating Bicycle Use

In the stated preference experiment respondents were asked to indicate how much the shown environment could stimulate them to cycle in general and how much it could stimulate them to cycle to the train station. Each respondent was asked to evaluate 6 situations. With 894 valid responses, which resulted in a dataset of 5364 observations. Respondents were given five answer options on a scale ranging from '- -' (to a very limited extent) to '++' (to a very large extent). Because the scale has a clear ordering in it, the dependent variable is an ordinal variable, and the most logical analysis method would be to use Ordinal Logistic Regression (OLR) to analyze the data. An OLR model estimates one equation for all response categories. The model therefore assumes that the slope coefficients are the same across response categories (UCLA: Statistical Consulting Group, n.d.-a). To check if this assumption is true and if the model is valid, a Test of Parallel Lines was executed in SPSS for both 'cycling'-variables. The output of these tests can be found in appendix F. The null hypothesis that the slope coefficients are the same is accepted if the significance of the Chi-Square value is larger than 0.05. For the 'Cycling in General'-variable the significance is 0.904, meaning that the model is valid and that an OLR can be executed. For the 'Cycling to the Train Station'-variable the model is also valid. The significance for this variable is 0.319, therefore the null hypothesis is accepted and the OLR can also be used. After the OLR, a Random Effects Model and Latent Class Model are executed for 'Cycling to the Train Station' in order to determine which model is the best fit for the data and to check for heterogeneity. Then, the classes generated by the Latent Class Model are further analyzed to see if certain (personal) characteristics could determine class membership. Afterwards, the results of both OLR's are compared and discussed.

Test of Independency

Before individual analyses of the variables 'Cycling to the Train Station' and 'Cycling in General' can be executed, it can be investigated if these variables are independent and heterogenous enough to analyze as two separate variables. A crosstab analysis was performed to test the hypothesis that the two variables are uncorrelated. The output of the crosstab analysis can be found in appendix G. The crosstabulation shows the expected count, which would be the count if the null hypothesis is true, and the actual count. The actual count is for all categories far off from the expected count, from which it can be derived that the variables are in fact highly correlated. The significance of the Chi-Square value confirms this. The Chi-Square is significant, which means that the null hypothesis is rejected and the variables are correlated. Kendall's tau-b value indicates the direction and strength of the relationship between ordinal variables (Laerd Statistics, 2018). The tau-b value is positive, which means that if the choice of category for the variable 'Cycling to the Train Station' gets higher, the choice of category for the variable 'Cycling in General' also gets higher. The tau-b value of 0.683 is considered a strong relationship between the variables.

Based on the crosstab analysis, it can be concluded that the results of the individual analyses will be quite similar and in theory only further research for one of the variables is necessary to get the general results of both variables. However, as this research wants to examine where the differences are between cycling in general and cycling to a train station, it is acceptable to perform both analyses and compare the results. Therefore, for both variables an Ordered Logit model is generated and the results will be compared. Considering that 'Cycling to the Train Station' is the main focus of this research, the analysis for this variable will be more in-depth and will include a Random Effects model and Latent Class model. Based on the outcome of the crosstab analysis, it is assumed that also executing these models for ‘Cycling in General’ will give similar results.

4.2.1 Cycling in General

To assess whether the degree of stimulating bicycle use is different for cycling to the train station compared to cycling in general, first the values related to cycling in general have to be determined. In this paragraph the analysis of the ‘Cycling in General’-variable is discussed. The stated preference data was analyzed using an Ordinal Logistic Regression. The output of the OLR model can be found in appendix H.

4.2.1.1 Ordered Logit Model

Considering the goodness-of-fit of the model, the log likelihood of -7481.30 is higher than the log likelihood of -8633.02 for the null model. This gives a LRS value of 2303.44, which is higher than the Chi-Square statistic of 26.296 for corresponding degrees of freedom. From this it can be concluded that the OLR model performs better than the null model. The McFadden Pseudo R^2 shows a poor fit for the data, with a value of only 0.133. The AIC is given for when models generated by the same dataset have to be compared. The AIC for this model is 14994.6 with an AIC/N of 2.795.

TABLE 6 CYCLING IN GENERAL – ORDERED LOGIT MODEL

Threshold	**Level**	**Value**	
Stimulation to cycle in general	--/-	0	
	-/+-	1.51165***	
	+-/+	3.08623***	
	+/++	5.24274***	
Attribute	**Level**	**Part-Worth Utility**	**Range**
Building Height	2 floors	0.27312***	0.49567
	4 floors	-0.05057	
	6 floors	-0.22255	
Building Type	Historic	-0.02764	0.28994
	Modern	-0.13115***	
	Mix	0.15879	
Openness of Façade	Closed	-0.13371***	0.25671
	Semi	0.12300***	
	Open	0.01071	
Front Garden	No	-0.16832***	0.27130
	30 cm	0.06534*	
	1.2 m	0.10298	
Distance to Buildings	2 m	-0.33890***	0.63904
	4 m	0.03876	
	6 m	0.30014	
Activity of Ground Floor	Little traffic	0.15197***	0.40740
	Moderate traffic	0.10346***	
	Much traffic	-0.25543	
Constant		2.66171***	
****, **, * → Significance at 1%, 5%, 10% level*			

The first values to explain the OLR model are the threshold values. These values are the borders between the categories based on the utility. The first border '--/-' is considered as 0 by Nlogit6. Figure 33 depicts these thresholds on a scale. The constant is the utility a person would have when none of the attributes in the model are taken into account. This utility constant is based on (unobservable) factors that are not included in the model. The constant corresponds to the category that would be chosen in a starting situation where the attributes are not yet considered. In this case the constant is 2.66. This falls between the threshold for -/+- and +-/+ and indicates that the chosen category would be the '+-' category. With equation 3 and the part-worth utilities (the β in the formula) given in Table 6, the utility for a given situation can be calculated. As an example the utility for profile 3 and individual *q* is calculated:

$$V_{3q} = \beta_{constant} + \beta_{2floo} + \beta_{mix} + \beta_{open} + \beta_{30cm\ garden} + \beta_{6m\ distance} + \beta_{muc\ \ traffic}$$

$$V_{3q} = 2.66171 + 0.27312 + 0.15879 + 0.01071 + 0.06534 + 0.30014 + (-0.25543)$$

$$V_{3q} = 3.21438$$

This value can then be put on the threshold scale to see how the respondent would evaluate the situation based on the values generated by the OLR. The utility of 3.21 falls between the thresholds of the '+-/+' category and the '+/++' category, which means that this alternative would be evaluated in the '+' category, as can be seen in Figure 33.

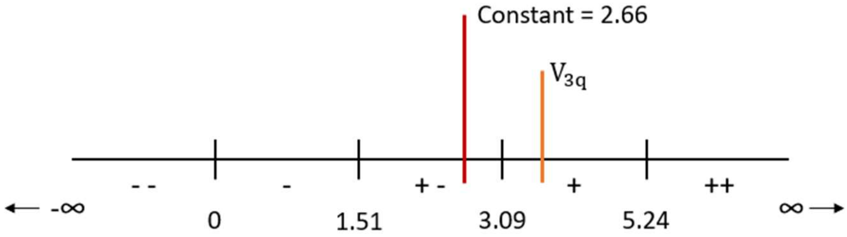

FIGURE 33 THRESHOLD SCALE FOR ORDERED LOGIT MODEL OF 'CYCLING IN GENERAL'

Table 6 shows the part-worth utilities for every attribute level generated by the OLR. Since Nlogit6 considers three confidence levels of significance, all levels with a p-value equal to or below 0.1 (90 percent confidence level) are considered significant. For each attribute at least one level is significant, which means that all attributes in some way contribute to the degree of stimulation of bicycle use in general. Looking at the part-worth utilities, a positive value (β>0) indicates that environments which contain that attribute level are more likely to be rated in the higher categories – in other words, they are more likely to stimulate bicycle use – whereas negative values (β<0) indicate that environments with that attribute level are more likely to be rated in the lower categories – i.e. they are less likely to stimulate bicycle use. The part-worth utilities of the first and second level are directly represented by the parameter estimates corresponding to the first and second level of each attribute in the Ordered Logit model. The part-worth utility of the third level of each attribute is not significant because it was not given by Nlogit6, but calculated afterwards. For this calculation equation 18 can be used:

$$3^{rd}_{parameter\ estimate} = \left(-1 \cdot 1^{st}_{parameter\ estimate}\right) + \left(-1 \cdot 2^{nd}_{parameter\ estimate}\right) \quad (18)$$

Graphs of the part-worth utilities per attribute can be found in appendix I. Regarding cycling in general people tend to get more stimulated to cycle when the buildings are low-rise with 2 floors, the façades are semi-open, there is a front garden present, and there is moderate to little traffic. The opposite effect is achieved when there are only modern buildings, the façades are closed, there is no front garden present, and there is only a small distance between the bicycle path and the buildings. The range for each attribute can show the relative contribution each attribute has to the degree of stimulating bicycle use in general in relation to the relative contributions of the other researched attributes. The relative contribution of the attributes can be seen in Figure 34. Distance from the bicycle path to the buildings has the largest contribution, then the height of the buildings, the activeness of the ground floor, the building types, the presence of a front garden, and the openness of the façades has the smallest contribution.

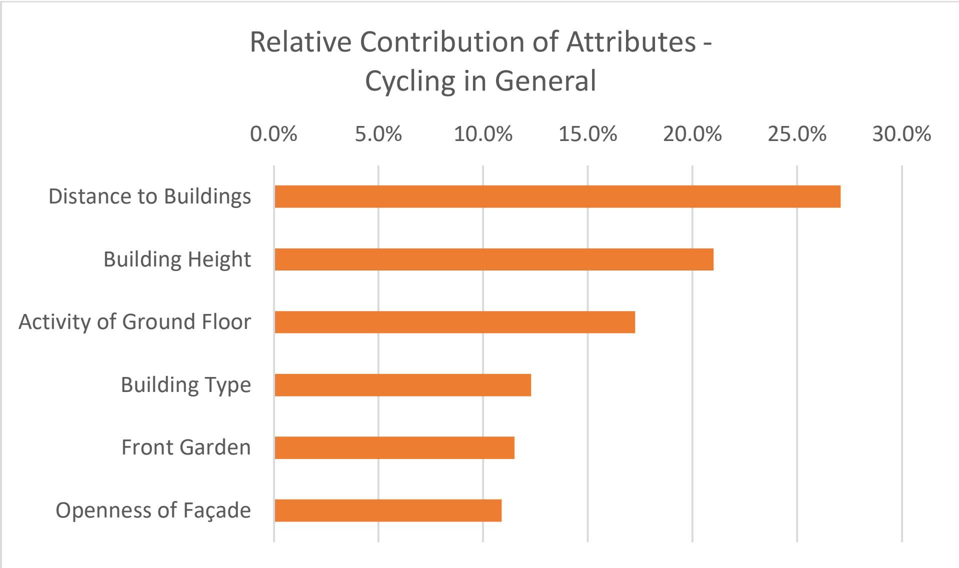

Figure 34 Relative contribution of the attributes on the evaluation of cycling in general

4.2.2 Cycling to Train Station

Now that the values for ‘Cycling in General’ have been determined, ‘Cycling to Train Station’ can be analyzed. Because ‘Cycling to Train Station’ is the main focus of this research, the analysis for this variable is more in-depth. Same as for ‘Cycling in General’, an Ordinal Logistic Regression analysis is executed. Additionally, a Random Effects Model and Latent Class Model are generated to determine if heterogeneity plays a role in the data. The Latent Class Model is then further analyzed to see if certain (personal) characteristics can determine class membership. Lastly, the two cycling-variables are combined for a linear regression to assess the contribution the building characteristics on the willingness to cycle when the average evaluation of the cycling-variables is taken.

4.2.2.1 Ordered Logit Model

The OLR model was carried out using Nlogit6. The full output of the model can be found in appendix H. The log-likelihood of -7178.77 of the estimated model is higher than the log-likelihood of the null-model of -8633.02, which means that the OLR model fits the data better than the null model. This is confirmed by the higher LRS of 2908.50 than the Chi-Square statistic of 26.296. The value of McFadden’s Pseudo R^2, on the other hand, is low with a value of 0.17. This means that the model is not a very good fit of for the observed data. To be able to later compare different models for goodness-of-fit, the Akaike Information Criterion (AIC) can be taken into account. For this model the AIC is 14389.5 with a corresponding AIC/N of 2.683.

TABLE 7 CYCLING TO TRAIN STATION – ORDERED LOGIT MODEL

Threshold	**Level**	**Value**	
Stimulation to cycle to the train station	--/-	0	
	-/+-	1.427***	
	+-/+	3.205***	
	+/++	5.386***	
Attribute	**Level**	**Part-Worth Utility**	**Range**
Building Height	2 floors	0.24345***	0.43356
	4 floors	-0.05334	
	6 floors	-0.19011	
Building Type	Historic	0.00878	0.27814
	Modern	-0.14346***	
	Mix	0.13468	
Openness of Façade	Closed	-0.11097***	0.21301
	Semi	0.10204***	
	Open	0.00893	
Front Garden	No	-0.13906***	0.21366
	30 cm	0.06446*	
	1.2 m	0.0746	
Distance to Buildings	2 m	-0.33935***	0.63016
	4 m	0.04854	
	6 m	0.29081	
Activity of Ground Floor	Little traffic	0.15229***	0.39948
	Moderate traffic	0.09490***	
	Much traffic	-0.24719	
Constant		3.05563***	
****, **, * ➔ Significance at 1%, 5%, 10% level*			

In paragraph 4.2.1.1 it was explained what the threshold values mean. The threshold scale for ‘Cycling to Train Station’ can be seen in Figure 35. The constant falls in the ‘+-‘ category with a value of 3.06, indicating that this is the base level choice of category if no attributes are included.

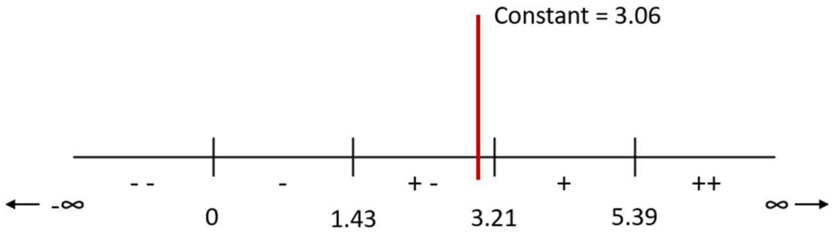

FIGURE 35 THRESHOLD SCALE FOR ORDERED LOGIT MODEL OF 'CYCLING TO TRAIN STATION'

In Table 7 the part-worth utilities of the attribute levels can be found. At least one of the levels is significant for each attribute, indicating that every attribute contributes to the degree of stimulation to cycle in general. As previously explained, the higher the part-worth utility for an attribute level the more likely the environment will be evaluated in a higher category, indicating that the environment stimulates bicycle use for trips to the train station more, and the lower the part-worth utility the more likely the environment will be evaluated in a lower category. The part-worth utilities of the first and second level are directly represented by the parameter estimates corresponding to the first and second level of each attribute in the Ordered Logit model. The part-worth utility of the third level of each attribute was seen as redundant by Nlogit6 and was calculated manually after the generation of the OLR model using equation 17. Graphs of the part-worth utilities for each individual attribute can be found in appendix I. The table shows that environments with low-rise buildings of 2 floors, buildings with semi-open façades, front gardens, and little to moderate traffic will stimulate people more to cycle to the train station. Modern buildings, buildings with closed façades, the absence of a front garden, and a small distance from the bicycle path to the building will discourage people to cycle. By calculating the range of each attribute it can be determined which attribute has the largest relative contribution to the degree of stimulating bicycle use and which attribute has the lowest relative contribution. As expected, the results are quite similar to the contributions of the attributes for cycling in general. Figure 36 shows that the contribution of the distance from the bicycle path to the building is the biggest, followed by the height of the buildings and the activeness of the ground floor. The building type, the openness of the façades, and the front garden contribute the least to the degree of stimulating bicycle use.

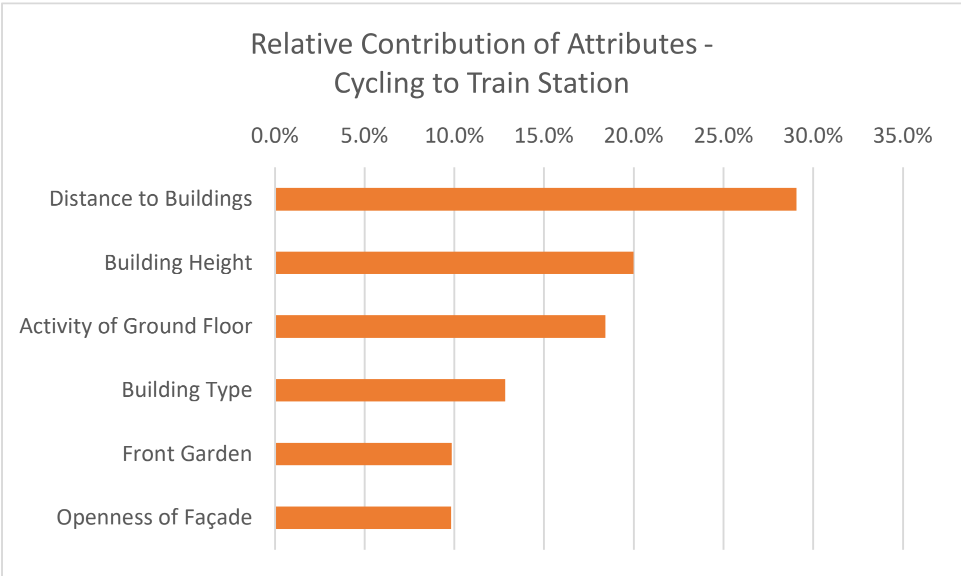

FIGURE 36 RELATIVE CONTRIBUTION OF THE ATTRIBUTES ON THE EVALUATION OF CYCLING TO THE TRAIN STATION

If not further specified in the setup of the model, the OLR estimates a fixed effects model. A fixed effects model assumes that the true effect size is the same in all studies that research the same topic. This means that it would not matter where the research is performed and what the sample draw is, the outcome would always be the same. Variations in the effect size can only be caused by sampling error (Borenstein et al., 2009). Considering this research, it is not likely that a fixed effects model will be the best fit for the data. Regardless of the sample drawn from the Dutch population being subject to sampling error (it is not representative of the population), there is another error that will cause less accurate results. Because the topic of the research is subjective and respondents' personalities play a role in the outcome, there might be variance in the results regardless of the location of research and the representation of the drawn sample for the entire population. It might therefore be better to use a random effects model.

4.2.2.2 Random Effects Model

A Random Effects model does not estimate one true effect, but estimates the mean of a distribution of effects based on the assumption that the true effect size varies per study. This also makes it possible to generalize the effects to other populations outside the sample, something that cannot be done using the fixed effects model as it only considers the identified population (Borenstein et al., 2009). In other words, the Random Effects model takes into account heterogeneity.

The Random Effects model was executed in Nlogit6. The full output of the model can be found in appendix J. It is important to first assess the goodness-of-fit of the model. The log likelihood of the model is -5381.23. This is higher compared to the null model with a value of -8633.02 and therefore it can be concluded that the random effects model is a better fit for the data than the null-model. The higher LRS value of 6503.58 compared to the Chi-Square statistic of 27.587 confirms this. The McFadden Pseudo R^2 value was not automatically calculated for this model, but can be obtained using equation 14. This gives a Pseudo R^2 of 0.377. This is above 0.3, indicating that the model is a decent fit for the data. To compare the model to for example the OLR model estimated earlier, the AIC and AIC/N can be taken into account. The AIC value is 10796.5 with a corresponding AIC/N of 2.013. The rule for good fit with the AIC is that the lower the value, the better the model. Both values are lower than the AIC and AIC/N for the OLR model. This means that the Random Effects model is a better fit than the OLR model, which means that heterogeneity plays a role in the data.

The threshold scale for the random effects model can be seen in Figure 37 along with the constant and the standard deviation. The constant has a value of 6.13 and with that it falls in the '+-' category, indicating that this is the base level choice of category if no attributes are included in the model.

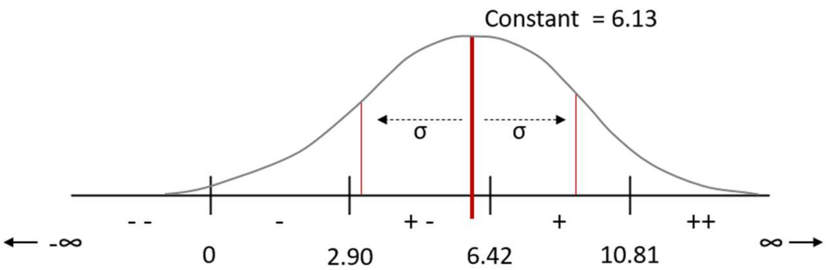

FIGURE 37 THRESHOLD SCALE FOR RANDOM EFFECTS MODEL OF 'CYCLING TO TRAIN STATION'

However, for the random effects model attention has to be paid to the σ-value: the standard deviation. According to Hensher et al. (2015, p. 813) in the random effects model only the constant is random. Combining the constant with the standard deviation would mean that the constant – the starting value for calculating the utility – varies for every individual. Therefore, the constant can for one person be very low whereas for another it is very high, corresponding to a negative or positive attitude as a starting point for evaluation of the shown environment. 68% of the respondents will fall within the range of one standard deviation from the constant, 95% will fall within two standard deviations, and almost all respondents (99.7%) fall within three standard deviations from the constant (Chandler, 2012), as illustrated in Figure 38.

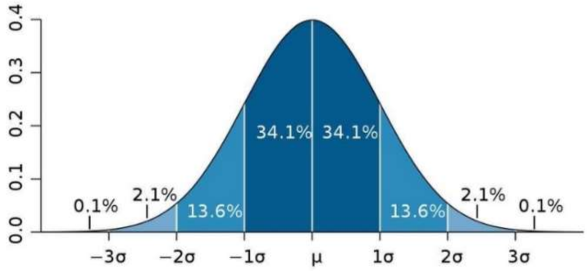

FIGURE 38 STANDARD DEVIATION (CHANDLER, 2012)

According to Field (2009) and Love (2019), a small standard deviation indicates that the value of the constant for every individual is close to the mean constant value. From that it can be derived that individual personal characteristics (e.g. personality) do not contribute to the evaluation of the shown environment much. The standard deviation generated by the random effects model however is quite large. This indicates that personal (unobservable) characteristics contribute to the evaluation of the environment to a large extent.

TABLE 8 CYCLING TO TRAIN STATION – RANDOM EFFECTS MODEL

Threshold	**Level**	**Value**	
Stimulation to cycle to the train station	--/-	0	
	-/+-	2.899***	
	+-/+	6.415***	
	+/++	10.814***	
Attribute	**Level**	**Part-Worth Utility**	**Range**
Building Height	2 floors	0.49732***	0.90341
	4 floors	-0.09123*	
	6 floors	-0.40609	
Building Type	Historic	0.01580	0.39222
	Modern	-0.20401***	
	Mix	0.18821	
Openness of Façade	Closed	-0.22547***	0.46541
	Semi	0.23994***	
	Open	-0.01447	
Front Garden	No	-0.27797***	0.46247
	30 cm	0.18450***	
	1.2 m	0.09347	
Distance to Buildings	2 m	-0.71124***	1.26914
	4 m	0.15334***	
	6 m	0.55790	
Activity of Ground Floor	Little traffic	0.33214***	0.80901
	Moderate traffic	0.14473***	
	Much traffic	-0.47687	
Constant		6.13322***	
Standard Deviation (σ)		3.09702***	
****, **, * → Significance at 1%, 5%, 10% level*			

In Table 8 the part-worth utilities for each attribute level can be seen as generated for the random effects model. What immediately stands out is that except for one attribute level ('Building Type – Historic') all attribute levels are significant. The signs before the part-worth utilities are the same as the signs in the OLR model. This means that there is no difference in the stimulation and discouragement of cycling for certain attribute levels compared to the OLR model except that more levels are now found significant. Low-rise buildings, semi-open façades, a front garden, and little traffic are still stimulating bicycle use, but now a further distance from bicycle path to buildings is also significant. Modern building types, closed façades, the absence of a front garden, and a close distance from bicycle path to buildings discourage bicycle use. Furthermore, the negative effect for buildings with 4 floors is now significant. By calculating the relative contribution of each attribute, it can be concluded that the contributions of the attributes are about the same for the random effects model compared to the OLR model. This is displayed in Figure 39. The order of the relative contributions of the attributes has changed in the random effects model. The three attributes that contribute the most are still 'Distance', 'Height', and 'Activeness', but now 'Openness' and 'Front Garden' have contribute more than in the OLR model. 'Type' has the lowest contribution, whereas it was ranked 4th on relative contribution based on the OLR model.

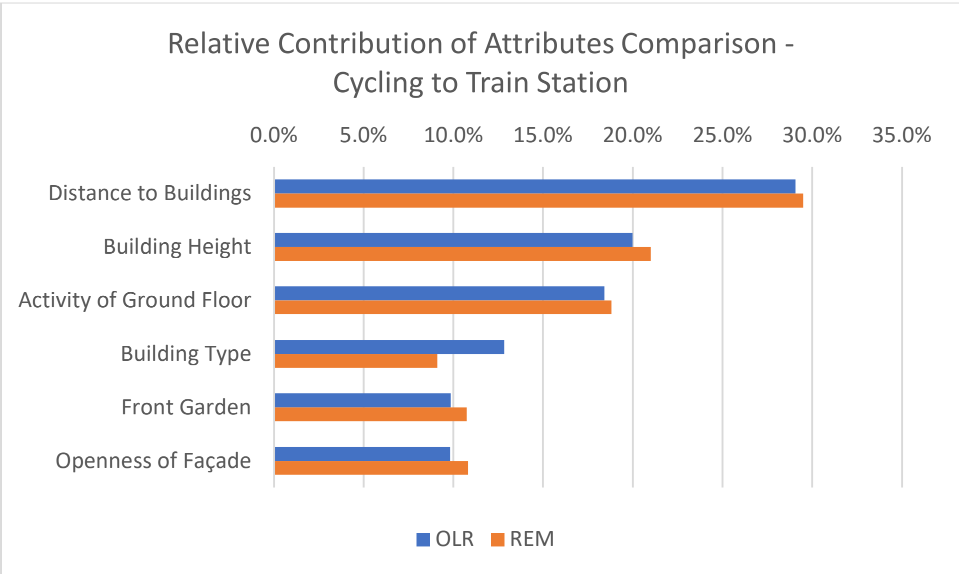

FIGURE 39 COMPARISON OF THE RELATIVE CONTRIBUTION OF THE ATTRIBUTES FOR THE OLR MODEL AND THE RE MODEL

4.2.2.3 Latent Class Model

A Latent Class (LC) Model was estimated using Nlogit6. A LC model uses panel data to identify which observations belong to the same individual and if individuals with similar preferences can be clustered in classes. This allows for the estimation of class specific parameters and the identification of heterogeneity between groups or respondents (Hensher et al., 2015). LC models with up to four classes were estimated, but the results quickly showed that only the 2-class model is valid, and therefore only two groups could be identified. The output of the LC model can be found in appendix K.

2-Class Latent Class Model

First, the goodness-of-fit of the 2-class LC model can be evaluated. The log likelihood of the LC model is -6057.76 which is higher than the null-model of -8633.02. This gives a LRS value of 5150.52, which is higher than the Chi-Square statistic of 47.400. This indicates the better fit for the latent class model. McFadden's Pseudo R^2 has a value of 0.298, which indicates a decent model fit. The AIC of the latent class model is 12181.5 with an AIC/N of 2.271.

TABLE 9 CYCLING TO TRAIN STATION – LATENT CLASS MODEL FOR 2 CLASSES

		Class 1	**Class 2**
Threshold	**Level**	**Value**	**Value**
Stimulation to cycle to the train station	--/-	0	0
	-/+-	2.82934***	1.46839***
	+-/+	4.53127***	4.50523***
	+/++	7.84173***	7.81051***
Attribute	**Level**	**Part-worth Utility**	**Part-worth Utility**
Building Height	2 floors	0.43360***	0.33549***
	4 floors	-0.12457*	-0.07513
	6 floors	-0.30903	-0.26036
Building Type	Historic	0.03703	-0.03014
	Modern	-0.09737	-0.18538***
	Mix	0.06034	0.21552
Openness of Façade	Closed	-0.22162***	-0.12171**
	Semi	0.17773***	0.17253***
	Open	0.04389	-0.05082
Front Garden	No	-0.15693**	-0.23397***
	30 cm	0.18358***	0.08873
	1.2 m	-0.02665	0.14524
Distance to Buildings	2 m	-0.66911***	-0.37135***
	4 m	0.23521***	-0.05079
	6 m	0.43390	0.42214
Activity of Ground Floor	Little traffic	0.19650***	0.22774***
	Moderate traffic	0.13381**	0.06944
	Much traffic	-0.33031	-0.29718
Constant		6.23179***	2.4091***
Class Probability		0.48673 (*49%*)	0.51327 (*51%*)
***, **, * ➔ Significance at 1%, 5%, 10% level			

Though the threshold values are approximately the same for both classes, the constant of class 1 is much higher than the constant of Class 2. Putting the constant on a threshold scale shows that the base level category for Class 1 is '+' (see Figure 40a for Class 1 and Figure 40b for Class 2). The members of this class can be characterized as more positive towards cycling in the shown environments than the members of Class 2.

The importance of the environment for Class 1 is confirmed by the significant values for almost all attributes and levels. Class 1 only showed insignificant results for 'Building Type', indicating that for Class 1 the building type does not contribute to the degree of stimulation of bicycle use caused by the environment. The distance from bicycle path to building is contributes most to the willingness to cycle for members of class 1. There is a strong negative estimate for the 2 meter distance, stating that class 1 is discouraged to cycle by small distances. The height also shows a clear stimulation to cycle for buildings with 2 floors. Lastly, compared to Class 2, Class 1 is more strongly discouraged by closed façades and find semi-open façades stimulating for cycling.

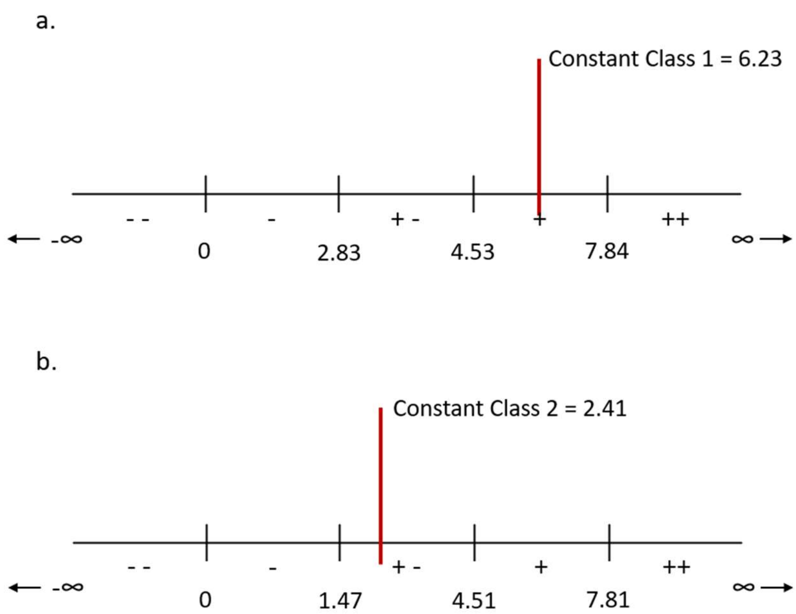

FIGURE 40 THRESHOLD SCALES OF LATENT CLASS MODEL FOR 'CYCLING TO TRAIN STATION'

The constant of Class 2 on the threshold scale in Figure 40b shows that the members of this class are more neutral in their evaluation, even slightly leaning towards the more negative categories. There are less levels significant, indicating that the look of the environment is less important for members of this class when it comes to cycling. Generally, the same stimulations and discouragements are shared with Class 1, though the estimates for Class 2 are more moderate for half of the attributes. The exceptions are for the absence of a garden which is slightly more negative for Class 2, although the difference is small. This also goes for the degree of stimulation to cycle for little traffic, which is higher for Class 2, but only slightly. A clear difference between Class 1 and 2 is that for Class 2 the building type is significant. The estimate shows a significant discouragement for cycling caused by modern building types.

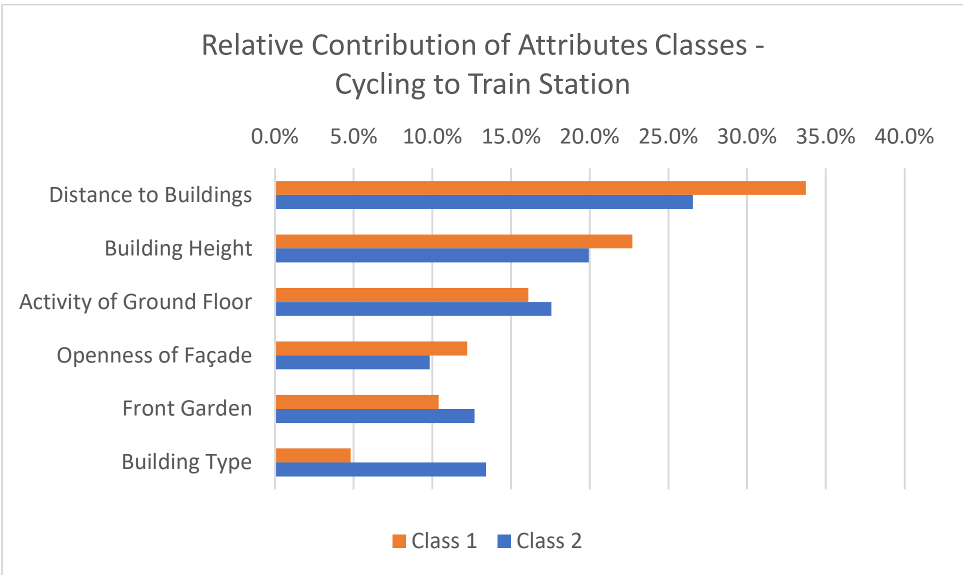

FIGURE 41 COMPARISON OF THE RELATIVE CONTRIBUTION OF THE ATTRIBUTES FOR CLASS 1 AND CLASS 2

The greatest differences between the classes can be observed when looking at the relative contributions of the attributes to the degree of stimulating bicycle use. Although 'Distance to

Buildings', 'Building Height', and 'Activity of the Ground Floor' are the most important attributes for both classes, the importance of the remaining attributes differs. Where for Class 1 'Openness of Façade', 'Front Garden', and 'Building Type' are important in the presented order, the order of importance of these three attributes for Class 2 is the exact opposite. It can also be observed that the attributes that are linked to spaciousness of the environment (Distance to Buildings, Building Height, and Openness of Façade) have a higher relative contribution for Class 1. Members of Class 1 can therefore be characterized as 'Space-seekers'. The only attribute that very distinctively has a higher contribution for Class 2 is 'Building Type', with a variety (mix) in building types leading to the highest evaluations of the environment. Members of Class 2 can therefore be characterized as 'Variety-valuers'.

4.2.2.4 Model Comparison

The executed models can be compared to determine which model fits the data best. Table 10 shows the values that determine the fit of the model. The highest log-likelihood can be found in the Random Effects Model along with the lowest AIC and AIC/N. These are indicators of good fit. For McFadden's Pseudo R^2 to prove an acceptable fit the value has to be 0.3 or higher. This is the case for both the Random Effects Model and the Latent Class Model. In general, the Random Effects Model proves to be the best fit out of all the executed models.

However, this research wants to look into the underlying groups and their characteristics when it comes to the decisions that were made. With knowledge about underlying groups and their corresponding characteristics, it will be possible to determine which characteristics are stimulating and discouraging bicycle use for target groups. Knowing the bicycle-stimulating building characteristics for a target group is beneficial for architects, urban designers, and policy makers, as they can optimize their plans and designs for the target group. Therefore, the study will look further into the Latent Class model to see if there are any (personal) characteristics that can be assigned to the classes.

TABLE 10 MODEL COMPARISON

Performance Determinant	Ordered Logit	Random Effects	Latent Class (2 Classes)
LL(0)	-8633.02	-8633.02	-8633.02
LL(β)	-7178.77	**-5381.23**	-6057.76
LRS	2908.5	6503.58	5150.52
Difference in number of parameters LL(β) and LL(0)	16	17	33
Chi-Square Statistic	26.296	27.587	47.400
McFadden's Pseudo R^2	0.17	**0.38**	**0.30**
AIC	14389.5	**10796.5**	12181.5
AIC/N	2.68	**2.01**	2.27

4.2.2.5 Membership of the Classes

In order to determine if (personal) characteristics are related to the subdivision between the two classes identified by the Latent Class Model, a Multinomial Logistic Regression analysis is executed. Essentially, because the classes form the dependent variable in the analysis, there are only two categories, which makes the Multinomial Logistic Regression analysis identical to a Binary Logistic Regression analysis and either one could have been executed, as they give the exact same results. To be able to perform this analysis, the respondents of the survey have to be assigned to one of the classes. For each respondent Nlogit6 has calculated the probability of class membership for both Class 1 and Class 2. The class that has the highest probability is assigned to the respondent. This led to an approximately even distribution of the classes among the respondents: 48.4% of the respondents were assigned to class 1 (the Space-seekers) and 51.6% to class 2 (the Variety-valuers). The logistic regression analysis was then executed using IBM SPSS Statistics. The choice was made to include eight variables – both personal and background characteristics of the sample – simultaneously in the analysis, because this will show which variables significantly contribute to membership probability and give 'best guess'-values for insignificant variables, which is useful for further application of the model as will be explained in paragraph 4.2.3. In the Multinomial Logistic Regression it is necessary to choose a reference category with regard to the latent classes. The choice for the reference category is based on the researcher's own preference. The general setting in Multinomial Logistic Regression is to take the last category as the reference category. There was no compelling reason to deviate from this setting, therefore Class 2 was chosen as the reference category. Consequently, the values that are found in the analysis for Class 1 are in comparison with class 2.

TABLE 11 PERSONAL CHARACTERISTICS LINKED TO CLASSES

Class 1[a] (Space-seekers)		**Estimate**
Gender	Male	-0.339**
	Female	0[b]
Age	Younger than 40 years	0.156
	40 to 59 years	-0.138
	60 years or older	0[b]
Education Level	Lower Education	-0.431**
	Higher Education	0[b]
Household Composition	Single (with or without children living at home)	-0.183
	With partner without children living at home	-0.154
	With partner and with children living at home	0[b]
Urbanity Level	Very Highly Urban	-0.069
	Highly Urban	-0.077
	Urban	-0.364
	Low Urban	-0.321
	Not Urban	0[b]
Bicycle Type	Standard Bicycle	0.141
	Electric Bicycle	0.154
	Other (including 'never cycle')	0[b]
Average Cycling Distance	20 km or less	-0.346**
	More than 20 km	0[b]
Distance to Train Station	5 km or less	0.358**
	More than 5 km	0[b]
****, **, * ➔ Significance at 1%, 5%, 10% level*		
a. The reference category is: Class 2. *b. This parameter is set to zero because it is redundant.*		

Eight variables are entered in the logistic regression analysis that possibly contribute to the probability of membership of a class. These variables are gender, age, education, household composition, level of urbanity, bicycle type, average cycling distance per week, and distance to the train station. Table 11 shows the estimates and significance of the variables and the full output of the analysis can be found in appendix L. The results reveal that four variables are significant for class membership.

First of all, gender is significant and has a negative estimate of -0.339 for males in Class 1. This indicates that the probability is higher for females to be Space-seekers and for males to be Variety-valuers. The next significant variable is education. The negative estimate of -0.431 for lower education in Class 1 shows that people with a higher education are more likely to be assigned to Class 1 and consequently people with a lower education to Class 2. The average cycling distance per week is also significant with a negative estimate for distances of 20 km or less. This means that there is a higher probability for people who cycle more than 20 km per week to fall into Class 1. The last significant variable is the distance to the train station. The positive estimate of 0.358 indicates that people who travel 5 km or less to the train station are more likely to be a member of Class 1.

To conclude, there is a higher probability for females, higher educated people, people who cycle more than 20 km per week, and people who live fairly close to the train station to be a Space-seeker (Class 1). The higher average cycling distance per week can be linked to the more positive view towards cycling for members of Class 1. In the LC model Class 1 also had more significant attribute levels, indicating that the environment is more determining in the respondents decision to cycle compared to Class 2. This can be explained by the close distance to the train station for members of Class 1. If people have to travel far to the train station the distance will become a more determining factor in the transportation mode decision and the environment will become less important.

Finally, age, household composition, level of urbanity, and bicycle type were not significant for the probability of membership of the classes.

4.2.3 Application of the Model

In the previous paragraph the part-worth utilities were calculated for personal characteristics to determine if a class consisted of certain types of people. With these utilities, the opposite can also be calculated: considering certain characteristics, what is the probability a person is a member of Class 1 or Class 2? Not all personal characteristics were found to be significant, but they will nevertheless be used to demonstrate the application of the model. The values of the insignificant part-worth utilities are considered ‘best guess’-values. Equation 9 is used to calculate the probability. This is demonstrated by taking a random person A with the characteristics presented in Table 12. In Table 13, the utilities with the calculated probabilities are given.

TABLE 12 PERSONAL CHARACTERISTICS FOR PERSON A

Person A	
Characteristics	**Level**
Gender	Male
Age	Younger than 50
Education Level	Low
Household Composition	Single (with or without children living at home)
Urbanity Level	Very strongly urban
Bicycle Type	Standard Bicycle
Average cycling distance per week	20 km or less
Distance from home to train station	Less than 5 km

TABLE 13 CLASS MEMBERSHIP PROBABILITY

Characteristic	**Value**	**Class 1**	**Class 2**
Gender	Male	-0.339	0.000
Age	< 50 years	0.156	0.000
Education Level	Low	-0.431	0.000
Household Composition	Single	-0.183	0.000
Urbanity Level	Very Strongly Urban	-0.069	0.000
Bicycle Type	Standard	0.141	0.000
Average cycling distance per week	< 20 km	-0.346	0.000
Distance from home to train station	< 5 km	0.358	0.000
Total Utility		-0.713	0.000
$e^{utility}$		0.490	1.000
Probability		0.329 (*32.9%*)	0.671 (*67.1%*)

Person A has a probability of approximately 33% of being a member of Class 1 and a probability of 67% of being in Class 2. It is therefore most likely Person A will be a member of Class 2 and will evaluate the building characteristics and the environments according to the part-worth utilities presented for Class 2 in the Latent Class Model.

When the demographic structure is known for an area that is to undergo redevelopment or there is a specific target group for new development, the model can be used to create guidelines for a design that encourages bicycle use in the area. When the target group mainly falls in Class 1, people responded more positively towards low-rise buildings. They dislike closed façades more than members of class 2 and they are stimulated to cycle by the distance between bicycle path and buildings being at least 4 meters. Finally, they respond positively to small front gardens. When the target groups falls in Class 2, as Person A in the example, modern buildings discourage cycling and a mix of building types would be advised. Furthermore, large distances of 6 meters between bicycle path and buildings are most stimulating for bicycle use. As opposed to Class 1, members of Class 2 respond positively to large front gardens. And finally, where for Class 1 moderate traffic is acceptable, Class 2 wants little traffic in the area. Class 2 will therefore respond better to traffic reducing measures.

4.2.4 Combining the Cycling-Variables

Because this research used a rating task, a Linear Regression could also be used, instead of an Ordinal Logistic Regression. This regression will transpose the categories '- -' to '++' to numerical scores ranging from 0 for the lowest evaluation to 4 for the highest evaluation. This creates a continuous score for a variable instead of a determination of a category. By combining the scores for 'Cycling to Train Station' and 'Cycling in General' a total combined score for the environment and how much it can stimulate people to cycle could be calculated, together with the contribution of each attribute and level to this combined score. However, it first has to be tested if the two variables are allowed to be combined based on homogeneity and scale reliability. Therefore, a reliability test is conducted. The output of this test can be found in appendix N. In this test the data from the 'Cycling to Train Station'-variable is compared to the data of the 'Cycling in General'-variable. Inter-item correlations and Cronbach's α are calculated. As defined by Piedmont (2014), inter-item correlations examine to which extent the scores on one item are related to the scores on all other items in a scale. The inter-item correlation should be above 0.4 for the variables to be homogeneous enough to combine. The value of the correlation between the two 'cycling'-variables is 0.741, which means that the variables are very homogenous. Cronbach's α measures how closely related a set of items are as a group – the internal consistency (UCLA: Statistical Consulting Group, n.d.-b). A Cronbach's α of 1 would mean that the results of the individual analyses for the variables would be exactly the same. Therefore, the closer Cronbach's α is to 1, the more similar the results of individual analyses will be and the more reliable the combined score will be. Field (2009) states that many sources consider a value of 0.7 or higher of Cronbach's α to be acceptable. For the 'cycling'-variables the value of Cronbach's α is 0.851. This value is very close to 1 and above the threshold of 0.7, and it can now be said that it is possible and appropriate to combine the data from the cycling variables to create a combined score, which is the average of the score for 'Cycling in General' and 'Cycling to Train Station' for every observation.

Linear Regression

The next step is to perform the Linear Regression. The full output of this analysis can be found in appendix N. First, the goodness-of-fit of the model is determined by examining the R^2-value and F-ratio with the corresponding significance. The R^2-value for the model is 0.053, which means that the independent variables account for 5.3% of the variation in the dependent combined cycling-variable. This is a small percentages and indicates that 94.7% of the variation in the combined cycling score cannot be explained by the independent variables alone. There have to be other variables that also influence the score (Field, 2009). For the F-ratio, the estimated model is compared to the mean-model, which assumes that the outcome is always the mean-value of the dependent variable and the independent variables do not influence this outcome (Field, 2009). Consequently, the null hypothesis is that the slope of the model line is 0. The F-ratio has a value of 25.045 and is significant at the 0.1%-level. Based on this, it can be concluded that the null hypothesis is rejected and therefore that the estimated model performs better than the mean-model.

Table 14 shows the coefficients for every attribute level generated by the Linear Regression. The coefficients for the first and second level are directly represented by the parameter estimates corresponding to the first and second level of each attribute in the Linear Regression model. The coefficients for the third levels were calculated using equation 17. The same levels show significance as in the Ordered Logit models for 'Cycling in General' and 'Cycling to Train Station'. This was expected, since the dependent variable in the Linear Regression is a combination of both cycling variables. Positive coefficients indicate that the score for the cycling-variable will increase if that particular level is present in the environment, whereas negative coefficients mean a decrease in the score. The model also shows similar results for certain building characteristics as were found in the Ordered Logit models. Low-rise buildings, a mix of building types, semi-open façades, the presence of a front garden, larger distances between bicycle path and buildings, and little to moderate traffic are more stimulating bicycle use. High-rise buildings, modern buildings, closed façades, the absence of a front garden, small distances from bicycle path to buildings, and much traffic on the other hand are discouraging bicycle use.

TABLE 14 COMBINED CYCLING-VARIABLE – LINEAR REGRESSION

Attribute	Level	Coefficient
Building Height	2 floors	0.135***
	4 floors	-0.024
	6 floors	-0.111
Building Type	Historic	0.001
	Modern	-0.072***
	Mix	0.071
Openness of Façade	Closed	-0.063***
	Semi	0.058***
	Open	0.005
Front Garden	No	-0.077***
	30 cm	0.036**
	1.2 m	0.041
Distance to Buildings	2 m	-0.180***
	4 m	0.021
	6 m	0.159
Activity of Ground Floor	Little traffic	0.071***
	Moderate traffic	0.059***
	Much traffic	-0.130
Constant		2.248***
****, **, * ➔ Significance at 1%, 5%, 10% level*		

4.2.5 Conclusion Stimulating Bicycle Use

Just as the crosstab analysis suggested, the results for 'Cycling in General' and 'Cycling to the Train Station' are similar. For both variables, the base level category respondents choose when the researched attributes are not yet included is the '+-' category, the most neutral category on the scale.

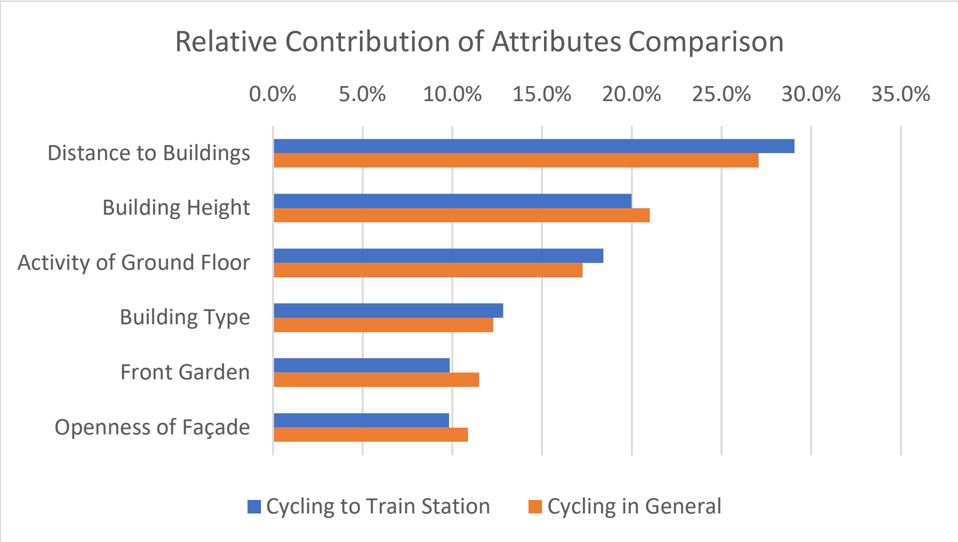

FIGURE 42 COMPARISON OF THE RELATIVE CONTRIBUTION OF THE ATTRIBUTES FOR 'CYCLING IN GENERAL' AND 'CYCLING TO TRAIN STATION'

The part-worth utilities for the attributes also shows similar values for 'Cycling in General' and 'Cycling to the Train Station'. Based on the outcome, it can be concluded that respondents are most stimulated to cycle by low-rise buildings, semi-open façades, the presence of a front garden, and little to moderate traffic. Respondents are discouraged to cycle by the presence of modern building types only, closed façades, the absence of a front garden, and small distances between bicycle path and buildings. In Figure 42 the relative contribution of the attributes to stimulating bicycle use is compared. Though the contributions are close together, this is where the differences between the variables can best be observed. The graph shows that 'Building Height', 'Front Garden', and 'Openness of Façade' are slightly more important for stimulating bicycle use in general, whereas 'Distance to Buildings', 'Activity of the Ground Floor', and 'Building Type' are the more important attributes for stimulating bicycle use to the train station. But again, these differences are minimal, as was expected based on the crosstab analysis.

Because the crosstab analysis indicated similar results and 'Cycling to the Train Station' is the main focus of this research, only for the 'Cycling to the Train Station'-variable a more in-depth analysis was conducted, with the assumption that in-depth analysis of the 'Cycling in General'-variable would lead to comparable results.

By comparing the Ordinal Logit Model, the Random Effects Model, and the Latent Class Model, it was concluded that the Random Effects Model is the best fit for the stated preference data in this research. This is most likely because this model takes into account the differences between individuals. Despite the lower fit compared to the Random Effects Model, a Latent Class Model was generated to identify groups within the sample. Two classes were identified. In general, both classes find the same characteristics stimulating and discouraging for cycling, but the part-worth utilities showed stronger values for Class 1 and more levels were significant. This indicates that Class 1 is impacted more by the environment compared to Class 2 when it comes to how much the environment can stimulate the respondents to cycle. The base level for Class 1 was also higher than for Class 2, which indicates that Class 1 beforehand has a more positive attitude towards cycling. A Multinomial Logistic Regression was executed to determine if there are (personal) characteristics that can be linked to the classes. From the eight variables that were entered in the analysis, four were significant and therefore contribute to the probability of class membership. These variables are gender, education, average cycling distance, and distance to train station. When the class membership of a target group can be determined, the design of an environment can be adjusted to the characteristics that stimulate cycling for that group. Based on the bicycle-stimulating and -discouraging characteristics, and relative contributions of the attributes as found in the Latent Class Model, design guidelines that stimulate bicycle use can be created for the development of areas.

A Linear Regression was used to investigate the contribution of the building characteristics to the combined score of both cycling-variables. Similar results were found in terms of stimulating and discouraging characteristics as for the Ordered Logit models of 'Cycling in General' and 'Cycling to Train Station' individually.

4.3 Model Estimation Experience of the Environment

To research how the building characteristic contribute to cyclists' experience of the environment, the evaluations regarding 'Attractiveness' and 'Bicycle-Suitability' were added to the experiment. In the stated preference experiment respondents were asked to indicate how attractive they found the shown environment and how suitable they found the environment for cycling. The dataset consisted of 5364 observations, as each of the 894 respondents were asked to evaluate 6 environments. Respondents were given five answer options on a scale ranging from '- -' to '++', with '- -' being 'Very unattractive/Very unsuitable for cycling' and '++' being 'Very attractive/Very suitable for cycling'. The research variables both have ordinal scales, so a test of parallel lines was performed to check if they could be analyzed using a Ordered Logit model (appendix F). Although the variable 'Attractiveness' passed the test of parallel lines, the variable 'Bicycle-suitability' did not. Because the intention was to compare the results for both variables the same type of analysis had to be executed. The most common and logical alternative for an Ordered Logit model is a Multinomial Logistic Regression model. The dependent variable is no longer treated as an ordinal variable but as a nominal variable – a variable with multiple categories that have no specific order. The MLR model calculates the part-worth utilities by comparing a category to a reference category. The reference category in this case is '+-' as this is the most neutral option to choose for evaluation. All the estimates are relative to this category. With category '+-' being the reference category, a negative value for a level in a category means that it is less likely that category will be chosen compared to the category '+-' if the shown environment contains that level, and the opposite is true for a positive value. So, positive values in the '+' and '++' categories mean that the corresponding attribute levels will lead to a higher evaluation of the environment and positive values in the '- -' and '-' categories mean that the corresponding levels will lead to a lower evaluation of the environment. After the analysis of the individual results for each variable, the results are compared and further discussed.

Test of Independency

Before starting a more detailed analysis of the variables 'attractiveness' and 'bicycle-suitability', it first was investigated if these variables were independent enough to analyze separately. The hypothesis that both 'experience'-variables are uncorrelated was checked by running a crosstab analysis with a Chi-Square test. The output of this analysis can be found in appendix G. The crosstabulation shows the expected count, which would be the count if the null hypothesis is true, and the actual count. Before even looking at the Chi-Square value, it can already be concluded that the actual count is in all cases far off from the expected count, leading to the assumption that the variables are correlated. This is confirmed by the significance of the Chi-Square value. The Chi-Square is significant, which means that the null hypothesis is rejected and the variables indeed correlated. Kendall's tau-b value is positive, which means that if the choice of category for the variable 'Attractiveness' gets higher, the choice of category for the variable 'Bicycle-suitability' also gets higher. The tau-b value of 0.452 is considered a relatively strong relationship. The outcome of the crosstab analysis suggests that because the variables are correlated, the results of the individual analyses will be quite similar.

Based on the crosstab analysis, it is fair to say that the results of the individual analyses will be similar enough to only further research one of the variables. However, as the test does not show a very high score, it might be interesting to see where the differences in the individual analysis results are. Therefore, for both variables a Multinomial Logistic Regression model is generated and the results will be compared.

4.3.1 Attractiveness of the Environment

Respondents were asked to evaluate the environments that were shown to them on attractiveness. To the respondents, attractiveness was explained as how pleasant they found the environment for cycling. In the experiment attractiveness is only related to the visual aspects of the environment since e.g. sound is not included. The collected data was analyzed using a Multinomial Logistic Regression model.

4.3.1.1 Multinomial Logistic Regression Model

The Multinomial Logistic Regression (MLR) model was estimated using SPSS. The full output of the model can be found in appendix M. First, the goodness-of-fit of the model has to be determined. This works slightly different in SPSS than in Nlogit6. The -2 log likelihood of the model is compared to the -2 log likelihood of the Intercept Only model. The -2 log likelihood of the model has a value of 406.933, which is closer to 0 than the -2 log likelihood of the Intercept Only model with a value of 966.634. The Chi-Square value is significant and therefore it can be concluded that the estimated model fits the data better than the Intercept Only model. Another method to determine the goodness-of-fit is by looking at the McFadden's Pseudo R^2. For the MLR model this value is 0.036, as calculated by SPSS. This is a very low value and the model fit can be considered poor.

The category-specific constants, or in official terms the Alternative Specific Constants (ASCs), need to be explained first. This is the start utility of a category compared to the reference category based on (unobserved) factors that are not included in the model. The constants are negative for all categories compared to the reference category (+-). This means that respondents are more likely to choose the '+-'-category based on factors outside the model.

Based on this it can be deduced that the respondents as a base level have a neutral attitude when it comes to evaluating the attractiveness of an environment.

The utility of the factors that are included in the model are not part of the constant but are expressed by the part-worth utilities. These part-worth utilities are the Beta estimates for every level. These can be found in Table 15.

TABLE 15 ATTRACTIVENESS – MULTINOMIAL LOGISTIC REGRESSION MODEL

		--	-	+-	+	++
Attribute	**Level**	**Beta**	**Beta**	**Beta**	**Beta**	**Beta**
Building Height	2 floors	-0.152*	-0.119**	0	0.320***	0.495***
	4 floors	-0.151**	-0.017	0	-0.075	-0.142
	6 floors	0.303	0.136	0	-0.245	-0.353
Building Type	Historic	-0.002	0.044	0	0.024	0.080
	Modern	0.103	0.036	0	-0.259***	-0.426***
	Mix	-0.101	-0.080	0	0.235	0.346
Openness of Façade	Closed	0.167**	0.112**	0	-0.109**	-0.234**
	Semi	-0.183**	-0.090*	0	0.049	0.151
	Open	0.016	-0.022	0	0.060	0.083
Front Garden	No	0.118	0.095*	0	-0.303***	-0.314***
	30 cm	-0.108	-0.043	0	0.019	-0.079
	1.2 m	-0.010	-0.052	0	0.284	0.393
Distance to Buildings	2 m	0.361***	0.219***	0	-0.234***	-0.356***
	4 m	-0.075	-0.057	0	0.048	-0.088
	6 m	-0.286	-0.162	0	0.186	0.444
Activity of Ground Floor	Little traffic	-0.031	-0.086*	0	0.143***	0.107
	Moderate traffic	-0.219***	-0.058	0	0.072	0.259***
	Much traffic	0.250	0.144	0	-0.215	-0.366
Constant		-1.333***	-0.212***	0	-0.369***	-1.903***
****, **, * → Significance at 1%, 5%, 10% level*						

4.3.2 Bicycle-Suitability of the Environment

Respondents were asked to evaluate the environments that were shown to them on bicycle-suitability. Bicycle-suitability was explained to respondents as how suitable they found the environment for cyclists. In the experiment bicycle-suitability is only related to the visual aspects of the environment. The collected data was analyzed using a Multinomial Logistic Regression model.

4.3.2.1 Multinomial Logistic Regression Model

The Multinomial Logistic Regression (MLR) model was executed in SPSS. The full output can be found in appendix M. Here again, the first step in interpreting the model is to determine the goodness-of-fit. The -2 log likelihood of the MLR model is 402.339. Instead of comparing this value to the null model, for the MLR model this value is compared to the Intercept Only model, which in this case has a value of 972.773. The -2 log likelihood of the MLR model is higher than the Intercept Only model and the Chi-Square value is significant. This means that the MLR model is a better fit for the data than the Intercept Only model. SPSS also generated the McFadden Pseudo R^2, which gave a value of 0.040. This is low and the model fit can be considered poor.

When looking at the results of the model, first the category-specific constants (ASCs) need to be discussed. The constant values are negative for all categories except the '+' category. This means that respondents are in general more likely to choose the '+-'-category compared to the categories with a negative constant, but are less likely to choose the '+-'-category compared to the '+'-category. From this it can be derived that the respondents as a base level have a moderately positive attitude when it comes to evaluating the suitability of an environment for cycling, influenced by factors that are not included in the model.

Next, the part-worth utilities are explained per attribute. The part-worth utilities can be found in Table 16.

TABLE 16 BICYCLE-SUITABILITY – MULTINOMIAL LOGISTIC REGRESSION MODEL

		--	-	+-	+	++
Attribute	**Level**	**Beta**	**Beta**	**Beta**	**Beta**	**Beta**
Building Height	2 floors	-0.065	-0.251***	0	0.094*	0.315***
	4 floors	-0.104	0.165**	0	-0.053	-0.067
	6 floors	0.169	0.086	0	-0.041	-0.248
Building Type	Historic	-0.188	-0.247***	0	-0.040	0.003
	Modern	0.108	0.159**	0	-0.014	-0.117*
	Mix	0.080	0.088	0	0.054	0.114
Openness of Façade	Closed	0.120	0.043	0	-0.076	-0.123*
	Semi	-0.305**	-0.142*	0	0.048	0.060
	Open	0.185	0.099	0	0.028	0.063
Front Garden	No	-0.135	-0.005	0	-0.061	-0.124*
	30 cm	-0.247*	-0.135*	0	0.016	0.020
	1.2 m	0.382	0.140	0	0.045	0.104
Distance to Buildings	2 m	0.453***	0.378***	0	-0.419***	-0.604***
	4 m	-0.103	-0.080	0	0.182***	0.144**
	6 m	-0.350	-0.298	0	0.237	0.460
Activity of Ground Floor	Little traffic	-0.118	-0.284***	0	0.220***	0.285***
	Moderate traffic	-0.174	-0.076	0	0.011	0.151**
	Much traffic	0.292	0.360	0	-0.231	-0.436
Constant		-2.362***	-1.012***	0	0.687***	-0.507***
****, **, * → Significance at 1%, 5%, 10% level*						

4.3.3 Comparison of Attractiveness and Bicycle-Suitability

In this paragraph the part-worth utilities of the attributes and levels for attractiveness and bicycle-suitability are compared. The utilities will be discussed per attribute and are visualized in graphs for a comprehensive overview of the MLR results.

Building Height

When looking at Figure 43, it can be concluded that for 'Attractiveness' buildings with a height of 6 floors are linked to a negative evaluation of the environment, whereas buildings of 2 floors lead to a positive evaluation. The '4 floors' level stays close to 0, which means that the impact of buildings with 4 floors on the level of attractiveness of the environment is minimal.

Although, 'Building Height' (Figure 44) fluctuates more for 'Bicycle-Suitability', the general conclusion is the same as for 'Attractiveness'. High-rise buildings (6 floors) will cause a negative evaluation of the environment, and low-rise (2 floors) will result in a positive evaluation. The part-worth utilities for the '4 floors' and '6 floors' levels for both variables are quite similar. However, it can be observed that the utility of '2 floors' is higher for 'Attractiveness'. From this it can be concluded that low-rise buildings have a higher impact on the evaluation of the attractiveness of the environment than on the perception of the bicycle-suitability.

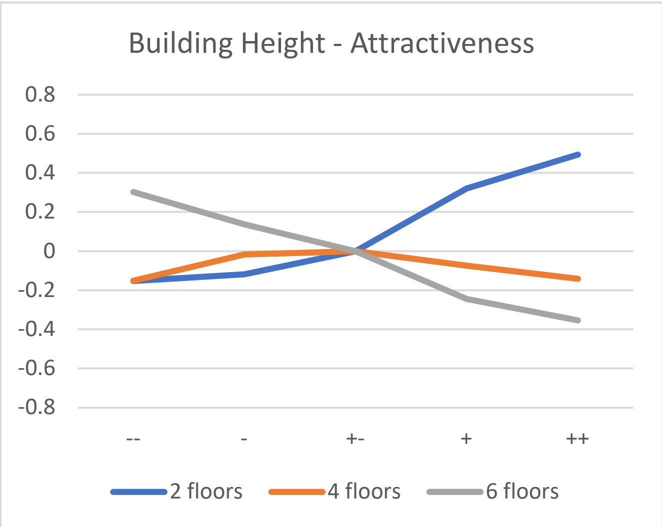

FIGURE 43 PART-WORTH UTILITIES FOR BUILDING HEIGHT – ATTRACTIVENESS

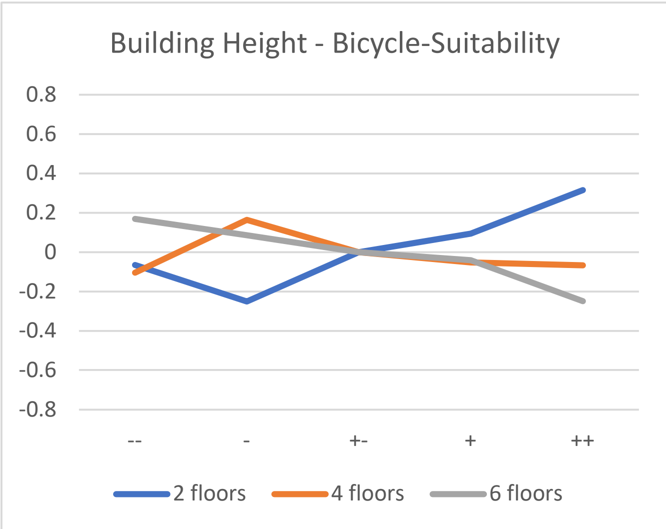

FIGURE 44 PART-WORTH UTILITIES FOR BUILDING HEIGHT – BICYCLE-SUITABILITY

Building Type

In Figure 45 it can be seen that for the evaluation of the attractiveness of the environment a mix of building types leads to a positive evaluation. Modern buildings are negative in the higher categories. This means that if an environment consists solely of modern buildings it will not be evaluated positively. Furthermore, it can be observed that modern buildings are more likely to be evaluated negatively and a mix of buildings less likely. However, the difference in the values of the part-worth utilities is not as large as for the higher categories.

For 'Bicycle-Suitability' the graph (Figure 46) shows that although a mix of building types will lead to a positive evaluation and modern buildings are less likely to lead to a positive evaluation, the part-worth utilities are close to 0 and therefore do not contribute to the evaluation much. Interesting is that for 'Bicycle-Suitability' historic buildings will not lead to a negative evaluation, yet the results do not show this positive evaluation for historic buildings in the higher categories.

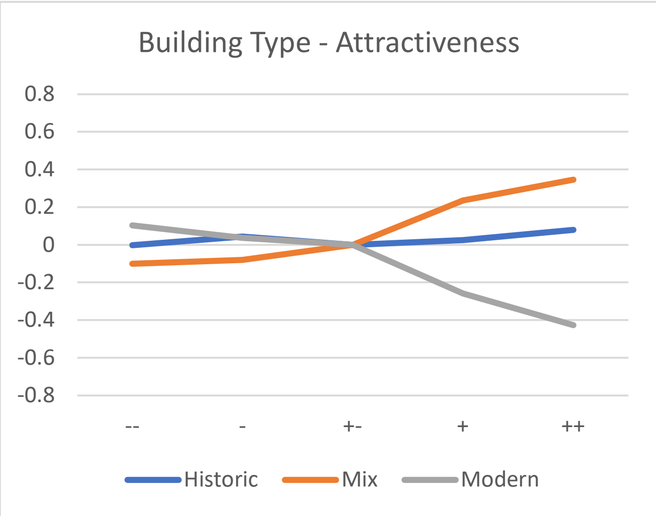

FIGURE 45 PART-WORTH UTILITIES FOR BUILDING TYPE – ATTRACTIVENESS

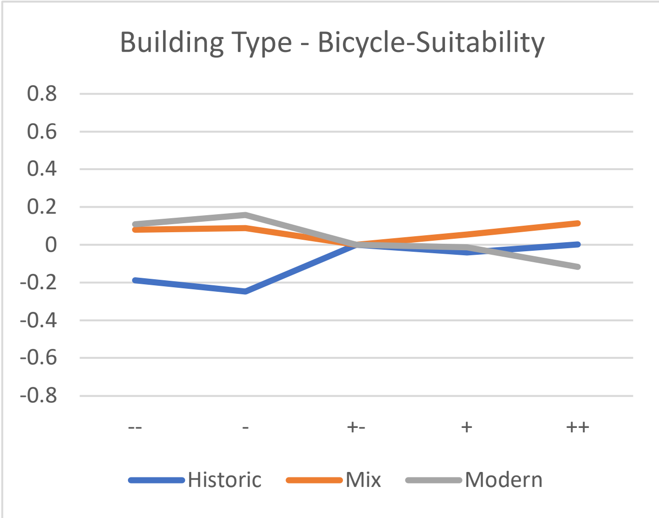

FIGURE 46 PART-WORTH UTILITIES FOR BUILDING TYPE – BICYCLE-SUITABILITY

Openness of the Façade

For 'Attractiveness' it can be concluded from the graph that closed façades will lead to a negative evaluation. Semi-open façades will lead to a positive evaluation. For 'Bicycle-Suitability' the results are similar. Closed façades will cause a negative evaluation and semi-open façades a positive evaluation. It is curious that open façades have positive part-worth utilities for (nearly) all categories for both 'Attractiveness' and 'Bicycle-Suitability', although these are not strong values. This could mean that cyclists are indifferent when it comes to the presence of open facades. Lastly, it should be mentioned that more part-worth utilities were found to be significant for this attribute for 'Attractiveness'. This could indicate that 'Openness of the Façade' is more important for the evaluation of the environment for the attractiveness compared to the bicycle-suitability.

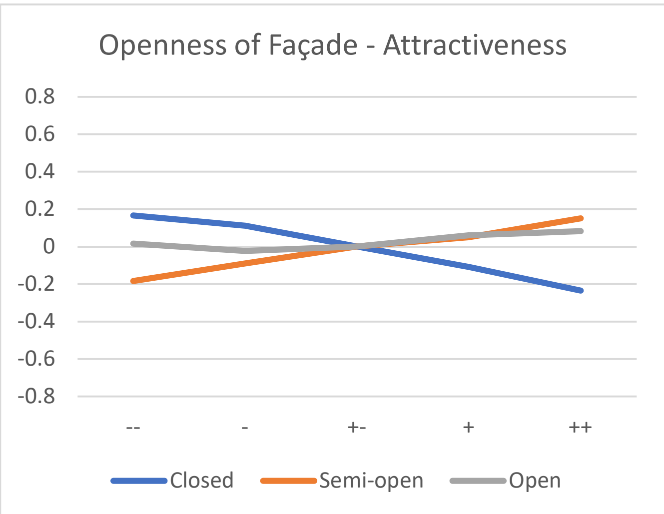

FIGURE 47 PART-WORTH UTILITIES FOR OPENNESS OF FAÇADE – ATTRACTIVENESS

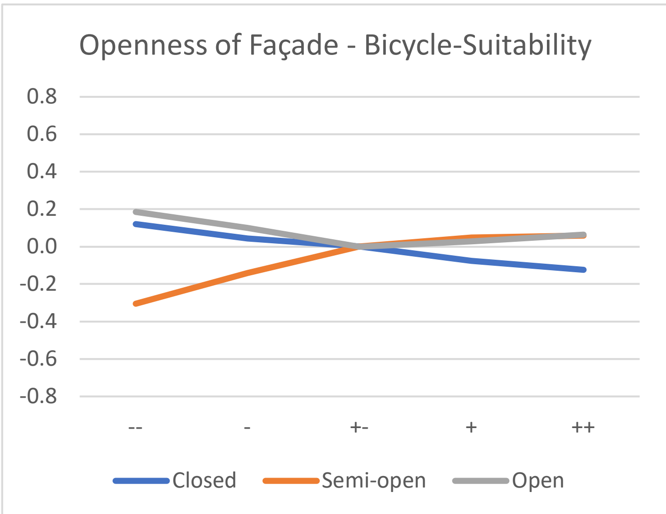

FIGURE 48 PART-WORTH UTILITIES FOR OPENNESS OF FAÇADE – BICYCLE-SUITABILITY

Front Garden

In the graph for 'Attractiveness' it is clear that a large front garden will lead to a high evaluation, whereas the absence of a front garden will results in a negative evaluation. For 'Bicycle-Suitability' on the other hand, a large front garden will most likely lead to a negative evaluation, although it is also the highest scoring level for the most positive category. The absence of a front garden scores negatively in the lowest and in the highest category. This indicates that for 'Bicycle-Suitability' cyclists have a neutral view towards the absence of a front garden. To be able to draw consistent conclusions from the results, the significance of the part-worth utilities is taken into account. For 'Attractiveness' the part-worth utilities for the 'No Front Garden' level are significant for the two highest categories. This means that the absence of a front garden will lead to a negative evaluation and that a front garden, regardless of the size, contributes to the attractiveness of an environment. For 'Bicycle-Suitability' the '30 cm Front Garden' level is significant for the two lowest categories. This indicates that if a small front garden is present the environment will not be evaluated negatively in terms of bicycle-suitability.

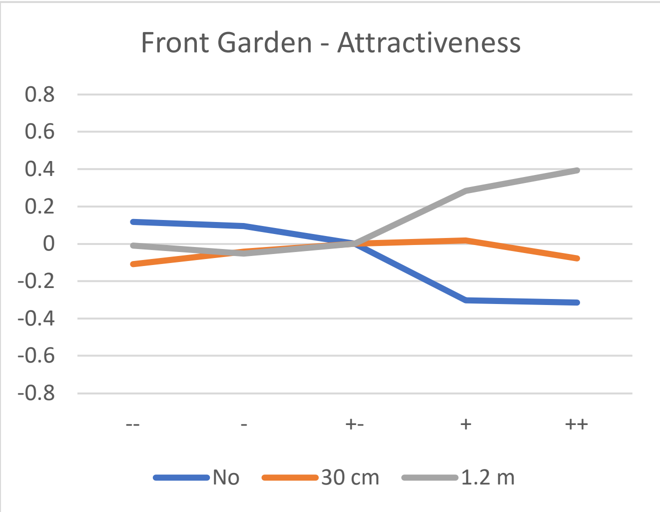

FIGURE 49 PART-WORTH UTILITIES FOR FRONT GARDEN – ATTRACTIVENESS

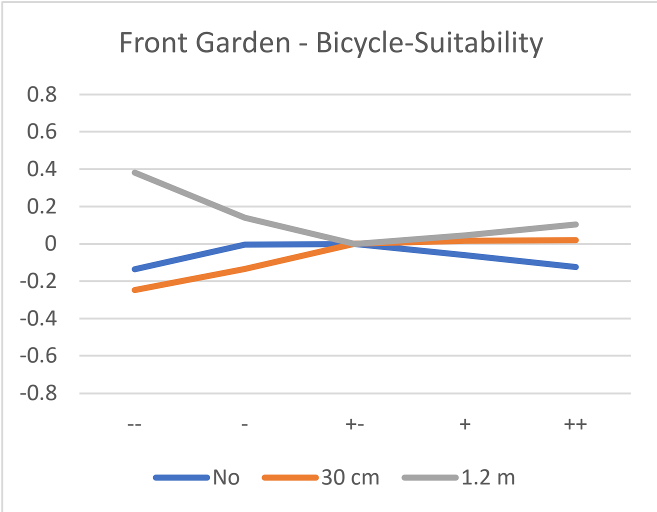

FIGURE 50 PART-WORTH UTILITIES FOR FRONT GARDEN – BICYCLE-SUITABILITY

Distance to Buildings

It can be observed for 'Attractiveness' that small distances will lead to a negative evaluation of the environment. The graph shows that the larger the distance the more positive the evaluation will be. The same goes for 'Bicycle-Suitability'. However, the dislike for the smallest distance is stronger for the evaluation of the bicycle-suitability of the environment. When examining the significance of the part-worth utilities for both variables, it can be seen that there are more utilities significant for 'Distance' for 'Bicycle-Suitability'. This indicates that the distance from bicycle path to buildings is a more important attribute for the evaluation of the environment on bicycle-suitability than it is for the attractiveness of the environment. On the other hand it should be stated that for 'Attractiveness' quite some part-worth utilities are also significant, which means that the distance is also important for the evaluation of the attractiveness of the environment.

FIGURE 51 PART-WORTH UTILITIES FOR DISTANCE TO BUILDINGS – ATTRACTIVENESS

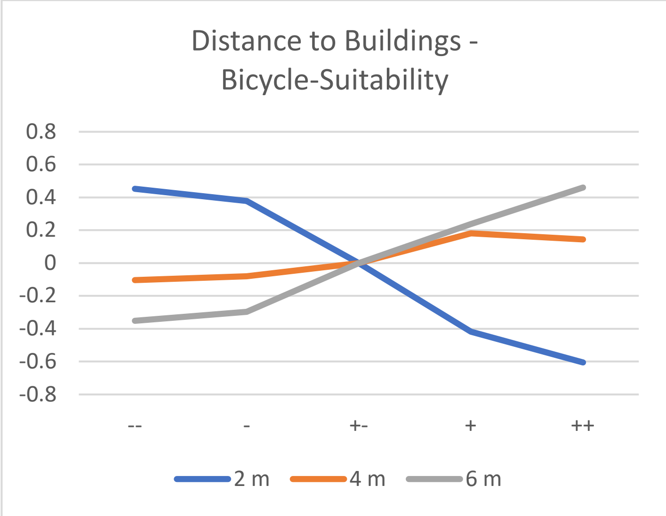

FIGURE 52 PART-WORTH UTILITIES FOR DISTANCE TO BUILDINGS – BICYCLE-SUITABILITY

Activity of the Ground Floor

The graph for ‘Attractiveness’ shows that ‘much traffic’ will lead to a negative evaluation of the environment. Furthermore, it can be concluded that little to moderate traffic makes an environment more attractive for cyclists, with a slightly higher evaluation for moderate traffic. For ‘Bicycle-Suitability’ a dislike for much traffic can also be identified. Here however, ‘little traffic’ make the environment more suitable for cycle compared to ‘moderate traffic’. When looking at the significance of the part-worth utilities, it can be seen that ‘little traffic’ has a higher significance for ‘Bicycle-Suitability’ than for ‘Attractiveness’, which could indicate that this is more determining in the evaluation of the bicycle-suitability of an environment than for the attractiveness.

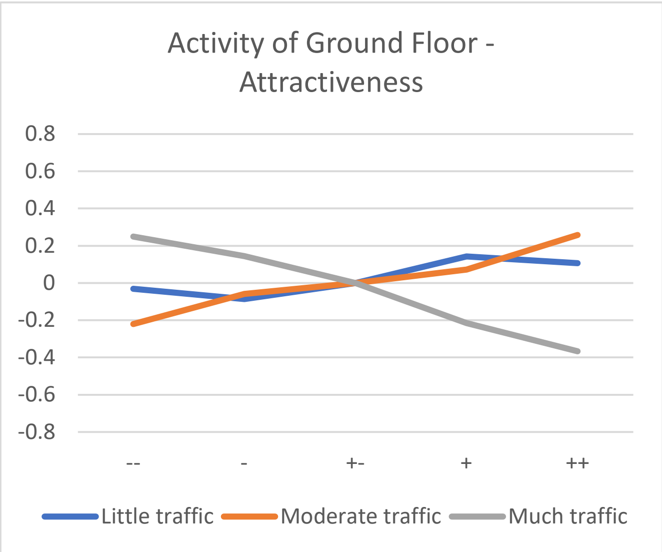

FIGURE 53 PART-WORTH UTILITIES FOR ACTIVITY OF GROUND FLOOR – ATTRACTIVENESS

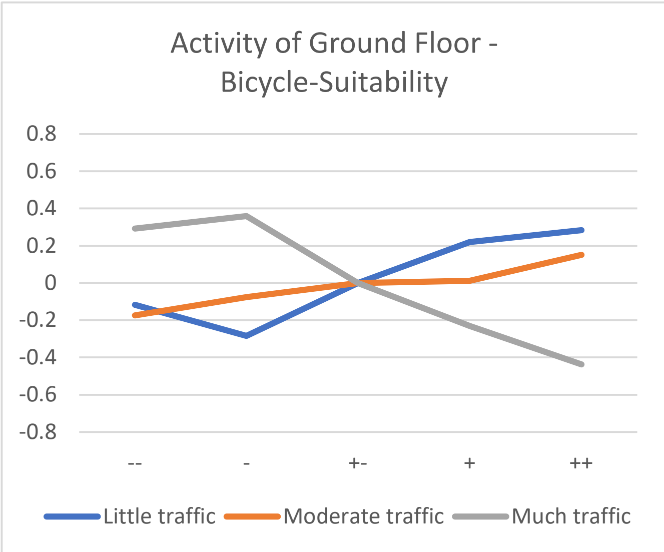

FIGURE 54 PART-WORTH UTILITIES FOR ACTIVITY OF GROUND FLOOR – BICYCLE-SUITABILITY

4.3.4 Combining the Experience-Variables

Same as for the cycling-variables, a Linear Regression could be used to calculate a combined continuous score for the experience-variables that indicates how much the building characteristics contribute to the experience of the environment (based on attractiveness and bicycle-suitability). A reliability test was executed to test if it is appropriate to combine the variables 'Attractiveness' and 'Bicycle-Suitability'. The output of this test can be found in appendix N. In this test the data from the 'Attractiveness'-variable is compared to the data of the 'Bicycle-suitability'-variable and inter-item correlations and Cronbach's α are calculated. The inter-item correlation should be above 0.4 for the variables to be sufficiently homogeneous. The value of the correlation between the two experience-variables is 0.533, which means that the variables are homogenous enough to combine. Cronbach's α measures the internal consistency (UCLA: Statistical Consulting Group, n.d.-b). A threshold-value of 0.7 is considered for reliability. The calculated Cronbach's α has a value of 0.693. Though this is below the boundary of 0.7, it is extremely close and it can therefore be considered acceptable to combine the data from the experience-variables for a combined total score. The combined score is the average of the score for 'Attractiveness' and 'Bicycle-Suitability' for each observation.

Linear Regression

Next, the Linear Regression was conducted. The full output of this analysis can be found in appendix N. The goodness-of-fit of the model is determined by looking at the R^2-value and F-ratio. The R^2-value for the model is 0.108, which means that the independent variables account for 10.8% of the variation in the dependent combined experience-variable. This means that 89.2% of the variation in the combined experience score cannot be explained by the independent variables and there have to be other variables that also influence the score (Field, 2009). The F-ratio has a value of 53.884 and is significant at the 0.1%-level. Consequently, the null hypothesis is rejected and it can be concluded that the estimated model performs better than the mean-model.

Table 17 shows the coefficients for every attribute level generated by the Linear Regression model for the experience-variable. The coefficients of the first and second level are directly represented by the parameter estimates corresponding to the first and second level of each attribute in the Regression model. The coefficients for the third levels were calculated using equation 17. As the Ordered Logit model was not allowed for the experience-variables, the Linear Regression model has to be compared to the Multinomial Logistic Regression models. As this is difficult due to the MLR models calculating part-worth utilities per category, it will be compared which building characteristics lead to a high and low evaluation. Positive coefficients in the Linear Regression model indicate that the score for the combined experience-variable will increase if that particular level is present in the environment, whereas negative coefficients mean a decrease in the score. For the combined experience-score, low-rise buildings, a mix of building types, semi-open façades, the presence of a front garden, large distances from bicycle path to buildings, and little traffic will increase the score. High-rise buildings, modern buildings, closed façades, the absence of a front garden, small distances from bicycle-path to buildings, and much traffic will cause the score to go down. Though in the Multinomial Logistic Regression model slight differences were found between 'Attractiveness' and 'Bicycle-Suitability', in general the results for the combined experience-variable are similar to the results of the individual analyses.

TABLE 17 COMBINED EXPERIENCE-VARIABLE – LINEAR REGRESSION

Attribute	Level	Coefficient
Building Height	2 floors	0.170***
	4 floors	-0.022
	6 floors	-0.148
Building Type	Historic	0.026
	Modern	-0.102***
	Mix	0.076
Openness of Façade	Closed	-0.078***
	Semi	0.076***
	Open	0.002
Front Garden	No	-0.089***
	30 cm	0.046***
	1.2 m	0.043
Distance to Buildings	2 m	-0.260***
	4 m	0.062***
	6 m	0.198
Activity of Ground Floor	Little traffic	0.115***
	Moderate traffic	0.074***
	Much traffic	-0.189
Constant		2.258***
****, **, * ➔ Significance at 1%, 5%, 10% level*		

4.3.5 Conclusion Experience of the Environment

When comparing the results for the attractiveness of the environment with the bicycle-suitability, it can be concluded that the results are quite similar, as was expected based on the crosstab analysis. Concerning ‘Building Height’ both variables show a positive evaluation for low-rise buildings and a negative evaluation for high-rise. It has to be mentioned that the values of the part-worth utilities are stronger for ‘Attractiveness’, indicating that the building height is slightly more important in the evaluation of attractiveness than for ‘Bicycle-Suitability’.

‘Building Type’ also has comparable results for both variables. There is a dislike for modern buildings, though for ‘Attractiveness’ there is an indication that a mix of building types leads to a positive evaluation, whereas this cannot be found for ‘Bicycle-Suitability’. On the other hand, historic buildings are not likely to score negatively for ‘Bicycle-Suitability’. This could not be concluded for ‘Attractiveness’.

Regarding ‘Openness of the Façade’ closed façades are evaluated negatively and semi-open façades positively for both variables. However, more significant part-worth utilities can be found for ‘Attractiveness’, which means that the openness of the façade is more important in the evaluation of the attractiveness of the environment than it is for the bicycle-suitability.

For ‘Front Garden’ the part-worth utilities indicate that the presence of a front garden regardless of the size is more relevant for the attractiveness of the environment than for the bicycle-suitability, though the part-worth utilities for ‘Bicycle-Suitability’ show that when a small front garden is present it is not likely that the environment will be evaluated negatively.

‘Distance to Buildings’ has proven to be one of the most determining attributes for both ‘Attractiveness’ and ‘Bicycle-Suitability’. Respondents significantly disliked short distances. For ‘Bicycle-Suitability’ more part-worth utilities were found to be significant compared to ‘Attractiveness’. From this it can be derived that ‘Distance to Buildings’ is more important for ‘Bicycle-Suitability’.

Finally, regarding ‘Activity of the Ground Floor’ it was found that little to moderate traffic leads to a positive evaluation for ‘Attractiveness’ with a slightly higher evaluation for moderate traffic compared to little traffic. Little traffic is more positive for ‘Bicycle-Suitability’. Much traffic was disliked for both variables. The presence of little traffic was more significant for ‘Bicycle-Suitability’, indicating that this attribute is more relevant for ‘Bicycle-Suitability’ than for ‘Attractiveness’.

Despite the results of the crosstab analysis, the choice was made to analyze both ‘experience’-variables separately to find where the differences in the evaluation of the variables are. It can be concluded that ‘Building Height’ and ‘Openness of the Façade’ are somewhat more relevant attributes for the attractiveness of the environment, whereas ‘Distance to Buildings’ and ‘Activity of the Ground Floor’ are more determining for the bicycle-suitability of the environment.

Finally, a Linear Regression was executed for the combined experience-variables. Though comparison with the Multinomial Logistic Regression models was a bit difficult due to the different structures of the models, it was found that the results from the Linear Regression model are quite similar to the results from the individual analyses.

4.4 Combining the Dependent Variables

So far, the dependent variables (‘Cycling in General’, ‘Cycling to Train Station’, ‘Attractiveness’, and ‘Bicycle-Suitability’) have been analyzed individually or in duos. However, the outcomes of the analyses showed similar results for all variables, with only small differences. As these dependent variables are all related to the appeal of an environment for cyclists, the scores of the dependent variables could be combined to create one overall score for the appeal of an environment for cyclists. The same approach is used as for the combining of the variables in paragraph 4.2.4 and 4.3.4. All four variables were researched using a rating task with the same categorical rating scale ranging from ‘- -‘ (to a very limited extent) to ‘++’ (to a very large extent). This makes it possible to perform a Linear Regression. The categories on the scale are transposed to numerical scores ranging from 0 for the lowest evaluation to 4 for the highest evaluation.

Before the Linear Regression can be executed, it first has to be investigated if it is allowed to combine the four variables based on homogeneity and scale reliability. Therefore, a reliability test is conducted. The output of this test can be found in appendix N. In this test inter-item correlations and Cronbach’s α are calculated. All inter-item correlations should be above 0.4 for the variables to be homogenous enough to combine (Piedmont, 2014). The lowest correlation value that can be observed in the inter-item correlation matrix is 0.533. This is above the threshold for homogeneity, which means that the variables are homogenous enough to combine. Cronbach’s α measures the internal consistency of the variables. A threshold value of 0.7 of Cronbach’s α is considered to be acceptable (Field, 2009). Cronbach’s α for the four variables combined is 0.868, which is above the threshold. Cronbach’s α if any of the variables are deleted from the test are all lower than the α for the four variables combined. Based on this and the inter-item correlations it can be concluded that it is possible and appropriate to combine the data from the four dependent variables to create an overall combined score. This score is calculated by taking the average score of the four variables for each observation.

Linear Regression

Now that combining the variables is allowed the linear regression can be performed. The full output of this analysis can be found in appendix N. The goodness-of-fit of the model is determined by examining the R^2-value and F-ratio. The R^2-value is 0.088, which means that the independent variables account for 8.8% of the variation in the dependent (combined) variable. This means that there have to be other variables that have an effect on the score, as 91.2% of the variation cannot be explained by the independent variables. The F-ratio has a value of 42.988 and is significant at the 1%-level. As a result, the null hypothesis is rejected, which means that the estimated model outperforms the mean-model.

TABLE 18 COMBINED DEPENDENT VARIABLES – LINEAR REGRESSION

Attribute	Level	Coefficient
Building Height	2 floors	0.153***
	4 floors	-0.023
	6 floors	-0.130
Building Type	Historic	0.014
	Modern	-0.087***
	Mix	0.073
Openness of Façade	Closed	-0.071***
	Semi	0.067***
	Open	0.004
Front Garden	No	-0.083***
	30 cm	0.041***
	1.2 m	0.042
Distance to Buildings	2 m	-0.220***
	4 m	0.042***
	6 m	0.178
Activity of Ground Floor	Little traffic	0.093***
	Moderate traffic	0.066***
	Much traffic	-0.159
Constant		2.253***
****, **, * → Significance at 1%, 5%, 10% level*		

Table 18 shows the coefficients for every attribute level generated by the Linear Regression. The coefficients of the first and second level are directly represented by the parameter estimates corresponding to the first and second level of each attribute in the Linear Regression model. The coefficients for the third levels were calculated using equation 17. Positive coefficients indicate that the score for the appeal of the environment for cyclists will increase if that particular level is present in the environment, and vice versa for negative coefficients. The model shows that the same attribute levels will lead to a positive or negative evaluation of the environment as was found in the individual analyses of the dependent variables. This was to be expected as the dependent variable in the Linear Regression model is the combination of the dependent variables of the individual analyses. Low-rise buildings, a mix of building types, semi-open façades, the presence of a front garden, larger distances between bicycle path and buildings, and little to moderate traffic will make the environment more appealing for cyclists. High-rise buildings, modern buildings, closed façades, the absence of a front garden, small distances from bicycle path to buildings, and much traffic will make the environment less appealing.

4.5 Discussion of the Results

In this chapter the results of the analyses were given. Regarding the representativeness of the sample the conclusion can be drawn that the sample is not representative for the Dutch population. Both 'Gender' and 'Urbanity Level' have a good distribution within the sample compared to the Dutch population. However, the distribution of 'Age', 'Education Level', and 'Household Composition' is not in line with the general Dutch population. A better representation of the Dutch population in the sample would make the results generalizable for the entire Dutch population.

Stimulating Bicycle Use

The conclusions for the contribution of the building characteristics on the degree of stimulating bicycle use will be given by answering research question 4 and 5, as defined in paragraph 1.2. Furthermore, the results will be discussed by comparing the outcome to the reviewed literature.

4. How do people evaluate the building characteristics in relation to the decision to cycle to train stations and can differences between groups of people be identified?

First of all, regarding the identified encouraging and discouraging characteristics, low-rise buildings are found to stimulate cycling. This is partly in line with the literature. Liu (2021) found that cyclists prefer buildings with four to six floors, however, the possible influence of the 'mere exposure effect' in this case has been previously mentioned, as this research was performed in one of the larger cities of China where high-rise is more common. Olde Kalter & Groenendijk (2018) concluded that Dutch cyclists have a dislike for high-rise buildings. This is similar to the results of this research, where high-rise has a negative part-worth utility.

Next, the analyses showed that the presence of a singular building type discourages cycling if it concerns modern buildings. This to some extent is supported by findings from the studies by Herzog & Shier (2000) and Ng (2020), who concluded that older buildings are preferred over modern buildings if physical conditions are similar, as is the case in this research. However, in this research there was no significant result for historic buildings, only a significant negative result for modern buildings. Instead, a mix of building types seems to be the most bicycle-stimulating level. This is in agreement with Lindal & Hartig (2013), who state that a street should not consist of a singular building type, but should have variation in architecture. The variation has a positive effect on the perception of the environment as it creates fascination.

Furthermore, a semi-open façade is stimulating for bicycle use, whereas a closed façade has a negative effect on cyclists' perception of the environment. Literature is divided on the topic of openness of the façade. Yammiyavar & Roy (2019) found in their study that people prefer large display windows, because it gives a view on the interior of the building. Although this research showed positive part-worth utilities for large windows, the values were so close to zero that the positive effect is negligible. Closed façades are mentioned by Gehl (2010) as a negative factor. They often lack detail and are monotonous, which makes the environment less interesting for spending time there by cyclists (and pedestrians). The negative effect of closed façades on the stimulation of bicycle use can also be associated with the level of activity and safety. When there are no windows present there is often little activity or only during certain hours of the day. A lack of activity makes people feel less safe. When people can see the activity inside buildings, even if there is no activity in the street, they feel safer because they know other people are close by.

Gehl (2010) and Liu (2021) both found that greenery has a positive effect on the perception the environment for cyclists and pedestrians. Liu observed that cyclists are more sensitive to greenery than pedestrians. The outcome of this research showed that the presence of a front garden has a positive effect on the stimulation of bicycle use, whether this garden is small or large. The absence of a front garden has a significant negative effect.

Regarding the distance from bicycle path to buildings, a discouraging effect for small distances was observed. The larger the distance, the more positive the effect on the stimulation of bicycle use. The reviewed literature has not said much on this topic, except Herzog & Shier (2000), who stated that far views of buildings are preferred over near views. This is in agreement with the results of the research, although it cannot be determined with the gathered data if this higher evaluation for large distances stems from a different observation of the buildings as is the case for Herzog & Shier (2000), or if it is related to factors that are not included in the research (e.g. safety).

When it comes to Activity of the Ground Floor, little to moderate traffic is most stimulating for bicycle use. Literature states that activity surrounding buildings has an influence on the appeal of an area and the feeling of safety. Commonly, streets with activity are chosen over deserted streets by cyclists (Gehl, 2010). This research does not include deserted streets and therefore the negative effect for deserted streets cannot be confirmed. What seems contradictory is that little traffic has the highest positive part-worth utility for both variables. Based on the literature it would be expected that cyclists find moderate to much traffic most encouraging. In this research the activity is linked to the buildings, however, in real life activity is also linked to safety. Much traffic is often regarded as unsafe and it is likely that respondents have taken this more into consideration in their evaluation than the activity linked to buildings.

The results regarding the encouragement and discouragement of bicycle use for the cycling-variables are summarized in Table 19.

The Random Effects model showed that heterogeneity plays a role in the dataset, but did not differentiate between groups of people. Therefore, a Latent Class Model was used for further analysis to determine if groups could be identified among the respondents and to see if there were certain characteristics that could be linked to these groups. Two classes were identified by the Latent Class Model. The largest differences between the classes are that for Class 1 more part-worth utilities are significant and many part-worth utilities have a stronger value than the part-worth utilities for Class 2, which indicates that people belonging to this group are more impacted by the environment when it comes to making the decision to cycle. Furthermore, people are more likely to be a member of Class 1 when they have a more positive attitude towards cycling, have to travel 5 km or less to the train station, have a higher average cycle distance per week (i.e. they cycle more), when they are female, and when they have a higher education. Based on the relative contribution of the attributes, Class 1 was characterized as ‘Space-seekers’. Contrarily, people are more likely to be a member of Class 2 when they have a neutral attitude towards cycling, live further than 5 km from the train station, have a lower average cycle distance per week, they are male, and they have a lower education. Class 2 is characterized as ‘Variety-valuers’, because of the significantly higher contribution of 'Building Type' and the bicycle-stimulating outcome for a mix of building types for this class.

The differences between the classes can to some extent be explained by the (personal) characteristics that were found in a Multinomial Logistics Regression to have a significant effect on the probability of class membership. For distance to the train station, the expectation was that when people have to travel 10 km or more to the train station, the distance becomes such an important factor in the transportation mode choice that the impact of the environment, and specifically building characteristics, becomes negligible. The larger travel distances are linked to Class 2, which could explain the lesser impact of the environment that is assumed by less significant and weaker part-worth utilities. It was also found that the average cycling distance per week is higher for Class 1. This can explain the more positive attitude towards cycling that was found for Class 1. The members of Class 1 cycle more in general and are therefore assumed to be more open towards cycling as a transport mode to the train station specifically.

With the values of the characteristic that were found to be significant for predicting class membership and 'best-guess' values for the insignificant characteristics class membership of an individual can be predicted, which can help in the creation of designs that stimulate bicycle use for specific target groups.

TABLE 19 OVERVIEW RESULTS FOR CYCLING VARIABLES

Attribute	Level	Cycling in General	Cycling to Train Station
Building Height	2 floors	+	+
	4 floors	0	0
	6 floors	-	-
Building Type	Historic	0	0
	Modern	-	-
	Mix	+	+
Openness of Façade	Closed	-	-
	Semi	+	+
	Open	0	0
Front Garden	No	-	-
	30 cm	+	+
	1.2 m	+	+
Distance to Buildings	2 m	-	-
	4 m	0	0
	6 m	+	+
Activity of Ground Floor	Little traffic	+	+
	Moderate traffic	+	+
	Much traffic	-	-

-	= discourages cycling
0	= neutral
+	= encourages cycling

5. Is there a difference in the evaluation of building characteristics for cycling in general and cycling to the train station?
The Ordinal Logistic Regression analyses of the variables 'Cycling in General' and 'Cycling to the Train Station' showed that the results of both analyses are quite similar and that there are no large differences in the evaluation. It was found that 'Building Height', 'Front Garden', and 'Openness of the Façade' are slightly more important for stimulating bicycle use in general, whereas 'Distance to Buildings', 'Activity of the Ground Floor', and 'Building Type' are the more important attributes for stimulating bicycle use to the train station. However, these differences are minimal and 'Cycling to Train Station' and 'Cycling in General' can be considered to generate similar results.

Experience of the Environment
To answer the last sub question of the research, the experience of the attractiveness and bicycle-suitability of the environment were examined.

6. Is there a relation between building characteristics and the evaluation of the attractiveness and bicycle-suitability of an environment?
Same as for the cycling variables, a crosstab analysis was executed to determine the relation between the two experience variables. Although this showed that the results of the analyses of the variables are similar, the relationship was not particularly strong and individual analysis would be interesting to find the differences between evaluations of the variables.

For both 'Attractiveness' and 'Bicycle-Suitability' all attributes show significant values for at least one level. The differences between the variables appear when looking at the strength of the estimates.

Regarding 'Building Height', the results for both variables are quite similar with low-rise buildings stimulating bicycle use and high-rise discouraging it. The higher part-worth utilities for 'Attractiveness' indicate that 'Building Height' is more relevant for the evaluation of the environment on attractiveness compared to bicycle-suitability. For 'Attractiveness', this is in line with the literature, which states that Dutch cyclists find high-rise less attractive (Olde Kalter & Groenendijk, 2018). Gehl (2010), furthermore, explained that low-rise is often evaluated more positively as it allows for the sun to reach the streets. The sunny look of the environment is also considered attractive. For 'Bicycle-Suitability' there is no clear connection to the literature. Lindal & Hartig (2013) state that high-rise buildings can create a sense of enclosure, which could be considered as unsuitable for cycling. However, this is not supported by literature. This sense of enclosure can simultaneously be connected to the positive evaluation for larger distances from bicycle path to buildings and low evaluation for small distances that were found to be important for both variables. Although 'Distance to Buildings' is important for 'Attractiveness' and 'Bicycle-Suitability', the part-worth utilities and significance indicate that this attribute is slightly more important for 'Bicycle-Suitability'.

Herzog & Shier (2000) and Ng (2020) found that people prefer modern buildings over older buildings, unless maintenance is accounted for. Somewhat contrary to the literature, this study found that for modern building lead to a lower evaluation regarding the attractiveness of the environment. Despite maintenance being controlled in this study, there is no significant result found for historic buildings. Architectural variation was expected to be the most attractive based on the study by Lindal & Hartig (2013), which is in line with the findings for attractiveness where a mix of building types is evaluated most positively.

Regarding ‘Openness of Façade’, the results showed a positive evaluation for semi-open façades and a low evaluation for closed façades for both variables. Façade openings are linked to activity and safety, and streets with closed façades often lack activity and are considered to be less safe (Gehl, 2010), which makes them unsuitable for cyclists. (Semi-)Open façades on the other hand provide more to look at, making the environment more attractive (Gehl, 2010). ‘Openness of Façade’ appeared to be more relevant for the evaluation of the attractiveness of the environment than for the bicycle-suitability.

For ‘Front Garden’, it was found that the absence of a front garden is reviewed negatively for the attractiveness of the environment. This is in agreement with the literature. Gehl (2010) stated that greenery in front of buildings can contribute to an interesting experience. In general, greenery is found to have a positive effect on the attractiveness of an environment (Bond, 2017; Van Dongen & Timmermans, 2019). For ‘Bicycle-Suitability’, greenery can be considered less positive. When trees and bushes are too close to the bicycle path it can create feelings of unsafety (Van Belois, 2016). In this research, a large garden was most likely to lead to a negative evaluation, which is a similar result as in the literature. However, this was not reflected by a large negative part-worth utility in the higher categories and in general people seemed to be indifferent for ‘Front Garden’ in terms of bicycle-suitability.

For ‘Activity of the Ground Floor’ is was concluded that it is a relevant attribute for both ‘Attractiveness’ and ‘Bicycle-Suitability’. Little to moderate traffic was found most attractive, and little traffic was evaluated most positively for bicycle-suitability. Gehl (2010) explained that people generally prefer streets with some activity over deserted streets, which is in line with the results for ‘Attractiveness’. For ‘Bicycle-Suitability’ literature is a bit divided. For example, Parkin et al. (2007) found that traffic volume has an influence on the bicycle-suitability of an environment, whereas Grudgings et al. (2021) concluded that traffic speed is more important and volume influences cycling only to a lesser extent. This research agrees with Parkin et al. (2007), as all traffic in the experiment had a fixed speed and the results show a more positive evaluation for little traffic. The results also indicated that ‘Activity of the Ground Floor’ is a more important attribute for ‘Bicycle-Suitability’ than for ‘Attractiveness’.

Overall, it can be concluded that ‘Openness of the Façade’ and ‘Front Garden’ are more relevant attributes for the attractiveness of the environment, whereas ‘Distance to Buildings’ and ‘Activity of the Ground Floor’ are more determining for the bicycle-suitability of the environment.

The results for the experience-variables are summarized in Table 20.

TABLE 20 OVERVIEW RESULTS FOR EXPERIENCE-VARIABLES

Attribute	Level	Attractiveness	Bicycle-Suitability
Building Height	2 floors	+	+
	4 floors	0	0
	6 floors	-	-
Building Type	Historic	0	+
	Modern	-	-
	Mix	+	+
Openness of Façade	Closed	-	-
	Semi	+	+
	Open	0	0
Front Garden	No	-	0
	30 cm	0	+
	1.2 m	+	0
Distance to Buildings	2 m	-	-
	4 m	0	+
	6 m	+	+
Activity of Ground Floor	Little traffic	+	+
	Moderate traffic	+	+
	Much traffic	-	-
-	= decrease		
0	= neutral		
+	= increase		

5. Conclusion, Discussion and Recommendations

5.1 Conclusion

This study has investigated to what extent building characteristics along the route to the train station can stimulate bicycle use in access trips. By examining the evaluation of cyclists of environments with varying building characteristics on the route from a starting point to the train station the degree of stimulation of bicycle use could be determined. The goal of the research was to gain more insight into the contribution of the environment, and particularly buildings, on the willingness to cycle in access trips. The results of this research can be used for creating and adjusting design policies, assessing existing environments, and assisting architects and urban designers in creating designs that stimulate bicycle use to train stations. The research goal resulted in the following main research question:

"To what extent do building characteristics along the route stimulate people to use the bicycle as an access mode to major public transport stations?"

A literature review and a stated preference experiment were used to answer the main research question. In the literature potentially stimulating building characteristics for bicycle use in access trips were identified. A selection of these building characteristics was included in the stated preference experiment.

Two cycling-variables were researched as dependent variables in Ordered Logit models: 'Cycling in General' and 'Cycling to Train Station'. The results of the estimated Ordered Logit model for 'Cycling to Train Station' showed that all the included building characteristics are significantly related to the stimulation of bicycle use, although not all levels are determinative for stimulating bicycle use in access trips. It is concluded that 'Distance to Buildings' (the distance from the bicycle path to the buildings) stimulates bicycle use to the largest extent relative to the other building characteristics when treating cyclists as a homogenous group. This is followed by 'Building Height' (the number of floors of the buildings), 'Activity of the Ground Floor' (the amount of activity/traffic in the street), 'Building Type' (whether all buildings are historic, modern or a mix of the two types), and 'Front Garden' (the absence or presence and size of a front garden). 'Openness of the Façade' (the size of the windows on the ground floor of the building) stimulate cycling to the smallest relative extent. With a Random Effects model and Latent Class model it was determined that there is heterogeneity between the respondents in the data. Two groups could be identified, Space-seekers and Variety-valuers, with differences regarding the building characteristics that stimulate cycling, although these differences showed not to be very distinctive. For the Space-seekers, the attributes that provide a spacious environment ('Distance to Buildings', 'Building Height', and 'Openness of Façade') are more determining in stimulating bicycle use. The main attribute that differentiates the Variety-valuers from the Space-seekers is 'Building Type', which is significantly important for the Variety-valuers and shows no significance for the Space-seekers. Some personal characteristics could be linked to membership of one of the groups. There is a higher probability for females, higher educated people, people who cycle more than 20 km per week, and people who live fairly close to the train station to be a Space-seeker.

The results of the Ordered Logit model for 'Cycling to Train Station' were compared to the Ordered Logit model for 'Cycling in General' to determine if there are differences in the building characteristics that stimulate cycling to the train station compared to cycling in general, as was claimed by Liu (2021). It was found that 'Building Height', 'Front Garden', and 'Openness of the Façade' are slightly more important for stimulating bicycle use in general, whereas 'Distance to Buildings', 'Activity of the Ground Floor', and 'Building Type' are the more important attributes for stimulating bicycle use to the train station. However, these differences are minimal and 'Cycling to Train Station' and 'Cycling in General' can be considered to generate similar results.

Additionally, two dependent variables related to the experience of the environment were investigated: 'Attractiveness' and 'Bicycle-Suitability'. It was concluded that building characteristics also have an effect on cyclists' experience of the environment. In general, the same results regarding which characteristics lead to a positive or negative evaluation were found in the Multinomial Logistic Regression models for the evaluation of the environment on attractiveness and bicycle-suitability as were found in the Ordered Logit models for 'Cycling in General' and 'Cycling to Train Station'. Because the research into the experience of the environment was a slight deviation from the main topic of the research, this was not investigated into further detail.

The conducted research adds to the scientific literature regarding the contribution of the environment on the willingness to cycle. Existing literature on the contribution of the environment on the willingness to cycle does not consider how buildings in general and separate characteristics of buildings in particular can stimulate cycling. In the literature review, building characteristics were identified that potentially stimulate bicycle use. A selection of these characteristics was included in this research. With the stated preference experiment and the analyses, the extent to which the researched building characteristics stimulate cycling was determined. The results can be considered a basis for the understanding of how buildings contribute to the willingness to cycle. Furthermore, the building characteristics that stimulate bicycle use identified for cycling to the train station and for cycling in general are similar and do not need to be investigated separately without definitive motive. This finding adds to the understanding of the willingness to cycle across different trip types. Additionally, the results of this research can be used in practice as will be discussed in the next paragraph.

5.2 Recommendations for Policy and Practice

The results of this research provide advice for policy makers, urban planners, architects and urban designers to create environments that stimulate bicycle use to train stations, and consequently increase train use and decrease car use.

First of all, policy makers have to pay attention to heterogeneity. This study proved that there are differences between people in which building characteristics stimulate cycling and policy makers should therefore not consider cyclists to be a homogenous group. Instead, it should be acknowledged that cyclists are a heterogeneous group and policies for cyclists should be designed likewise. In terms of design policies for cyclists when the target group mainly consists of females, higher educated people, or the distance to the train station is fairly small, it is recommended to include more zones in which high-rise is restricted, to increase distances for the building line, and to set minimum boundaries for the openness of façades along possible cycling routes. When the target group consists mainly of males, lower educated people, or when the distance to the train station is quite large, attention should be paid to the creation of diversity in building types along possible cycling routes.

Urban planners should use the contribution of the building characteristics and corresponding attribute levels to the willingness to cycle to evaluate existing cycling routes to train stations. By examining the building characteristics on a route, success factors can be determined and points of improvement can be identified. This can pinpoint were adjustments have to be made in order to attract more cyclists.

Finally, architects and urban designers need to identify the target group of the area they are designing for, as was demonstrated in the application of the model. Consequently, they can base their design on the building characteristics that stimulate bicycle use for the majority of the target group. If the target group mainly consists of Space-seekers, the focus should be on elements in the design that create a spacious, open environment, such as larger distances between bicycle path and buildings, low-rise buildings, and (semi-)open façades. Space-seekers are more likely to be females, higher educated people, people who cycle more than 20 km per week, and people who live fairly close to the train station. For Variety-valuers a design that consists solely of modern buildings should be avoided. Variety-valuers are more likely to be males, lower educated people, people who don't cycle many kilometers per week, and people who live quite far away from the train station. If it is not possible to identify a specific target group when starting the design, the results of the Ordered Logit model are the design guidelines. This means that large distances between bicycle path and buildings, low-rise buildings, activity-limiting measures, variety in building types, presence of a front garden, and avoiding closed-façades are advised design guidelines.

It has to be mentioned that this advice is exclusively focused on the researched building characteristics. For optimal bicycle-stimulating designs the excluded building characteristics should also be researched and other factors that contribute to the willingness to cycle should be taken into account, such as bicycle infrastructure, traffic calming measures, and road-side greenery.

5.3 Discussion of the Project

This research offers insight into the contribution of building characteristics on the willingness to cycle for cycling trips in general and more specifically to the train station. Additionally, it shows how the building characteristics affect a cyclist's experience of the environment, with a focus on the attractiveness and bicycle-suitability of the environment.

The literature review provided an extensive list of potentially stimulating building characteristics. The number of characteristics was too high to include all characteristics in the study and not all characteristics were suitable for the stated preference approach with simulated environments. A selection was made, which means that not all potentially stimulating building characteristics were researched. To increase the knowledge about the contribution of building characteristics on the willingness to cycle, the excluded characteristics could be investigated in future studies.

This study has proven that building characteristics play a role in stimulating bicycle use. However, for future research it would be useful to investigate how building characteristics relate to other aspects of the environment (e.g. infrastructure) in terms how much they can stimulate cycling and examine if building characteristics are significantly important when other environmental aspects are not fixed in the experiment. Moreover, it was only researched how building characteristics relate to the stimulation of bicycle use. As the goal is to increase the use of sustainable transportation modes, the research could be repeated for other modes (e.g. walking). The same goes for the public transport station, which was solely the train station in this research as the train can be considered the most important alternative transportation mode for larger distances and therefore has the most potential to decrease car use. The research could be extended to bus, tram, and metro stations, as these public transport stations differ from the train station (e.g. in distance and frequency) and could generate different results for how stimulating building characteristics are in the willingness to cycle.

Furthermore, the research was conducted in the Netherlands. This means that the building characteristics that were included are based on examples of how they appear in the Dutch environment. Additionally, conducting the research in the Netherlands also points to some Dutch specific aspects for train stations in urban areas, such as the location in the center of the city and consequently, the presence of high density areas surrounding the train station. The simulated environments are modeled after an urban environment, although this was not specifically mentioned to the respondents. It would be interesting to investigate if there are differences in the evaluation of building characteristics in urban versus rural environments.

Additionally, the Netherlands is known as a bicycle-oriented country and therefore the values given to bicycle aspects and characteristics of the environment by Dutch citizens may vary greatly compared to other countries. The results of this research will therefore not be applicable to other countries without first investigating if the evaluations of certain building characteristics along the route to a train station are similar to the Dutch evaluations.

It has to be mentioned that the sample used in this research is not representative for the Dutch population. A better representation of the Dutch population in the sample would make the results generalizable for the entire Dutch population.

Lastly, there are two points for the modelling and presentation of the simulated environments that could provide a more realistic cycling experience. Firstly, other senses than solely vision could be added to the simulations. Especially the addition of sound has the potential to improve the experience. However, close attention has to be paid to the reasoning why other senses are added, as these could also distract the respondents from the aspects that are researched or can unnecessarily complicate the experiment. And secondly, this research used videos that could be viewed on computer or mobile phone. VR technology could provide a more realistic and more immersive cycling experience.

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Appendices

Appendix A – Building Characteristics Derived from Literature

Category	Attributes	Literature
Building Height	Building height Number of floors	(Claxton, 2019; Gehl, 2010; Lindal & Hartig, 2013; Liu, 2021; Olde Kalter & Groenendijk, 2018)
Building Style	Individual buildings Entropy/architectural variation Building type Building diversity Building frontage	(Azma & Katanchi, 2017; Bond, 2017; Claxton, 2019; Gehl, 2010; Herzog & Shier, 2000; Ng, 2020)
Building Function	Active ground floor Building function Function diversity Transparency Land use mix	(Azma & Katanchi, 2017; Gehl, 2010; Liu, 2021; Mo et al., 2018; Nasar, 1994; Olde Kalter & Groenendijk, 2018)
Façade Openings	Display windows Narrow units Number of doors Entrance Number of openings Size of openings	(Gehl, 2010; Herzog & Shier, 2000; Stamps, 1999; Yammiyavar & Roy, 2019)
Complexity	Complexity Detailed façade Diversity of elemental shapes Ornamentation of façade Columns	(Akalin et al., 2009; Bond, 2017; Gehl, 2010; Herzog & Shier, 2000; Ikemi, 2005; Lindal & Hartig, 2013; Nasar, 1994; Ng, 2020)
Order	Organization Symmetry Repetitive patterns Order Rhythm of façade Vertical/horizontal elements Contrast Curves in façade Variation in depth Volume broken up Number of vertices	(Azma & Katanchi, 2017; Gehl, 2010; Herzog & Shier, 2000; Nasar, 1994; Ng, 2020; Stamps, 1999; Yammiyavar & Roy, 2019)

Materials	Materials	(Azma & Katanchi, 2017; Gehl, 2010; Nasar, 1994; Ng, 2020; Van de Kuil, 2017)
	Uniformity in materials	
	Colors	
	Texture	
	Natural/man-made materials	
Maintenance	Upkeep	(Azma & Katanchi, 2017; Herzog & Shier, 2000; Ng, 2020)
	Maintenance	
	Neglect	
	Physical condition	
Edge Zone	Edge zone	(Azma & Katanchi, 2017; Claxton, 2019; Gehl, 2010; Liu, 2021; Olde Kalter & Groenendijk, 2018)
	Interaction inside/outside	
	Furniture	
	Front garden	
	Greenery	
	Height differences with street level	
	Steps	
	Activity	
Other	Roof type	(Lindal & Hartig, 2013)
	Shadows	(Ikemi, 2005; Nasar, 1994)
	Viewing distance to building	(Herzog & Shier, 2000; Stamps, 1999)
	Length of façade	(Gehl, 2010)

Appendix B – Treatment Combinations

Profile	Height	Type	Openness	Front Garden	Distance	Activity
1	2 Floors	Historic	Closed	No garden	2 m	Little traffic
2	2 Floors	Modern	Semi-open	1,2 m	4 m	Moderate traffic
3	2 Floors	Mix	Open	30 cm	6 m	Much traffic
4	4 Floors	Historic	Semi-open	30 cm	4 m	Much traffic
5	4 Floors	Modern	Open	No garden	6 m	Little traffic
6	4 Floors	Mix	Closed	1,2 m	2 m	Moderate traffic
7	6 Floors	Historic	Open	1,2 m	4 m	Little traffic
8	6 Floors	Modern	Closed	30 cm	6 m	Moderate traffic
9	6 Floors	Mix	Semi-open	No garden	2 m	Much traffic
10	2 Floors	Historic	Open	30 cm	2 m	Moderate traffic
11	2 Floors	Modern	Closed	No garden	4 m	Much traffic
12	2 Floors	Mix	Semi-open	1,2 m	6 m	Little traffic
13	4 Floors	Historic	Closed	1,2 m	6 m	Much traffic
14	4 Floors	Modern	Semi-open	30 cm	2 m	Little traffic
15	4 Floors	Mix	Open	No garden	4 m	Moderate traffic
16	6 Floors	Historic	Semi-open	No garden	6 m	Moderate traffic
17	6 Floors	Modern	Open	1,2 m	2 m	Much traffic
18	6 Floors	Mix	Closed	30 cm	4 m	Little traffic

Appendix C – Twinmotion Settings

Character Paths

Type	Setting	Value
Pedestrian	Type	Multi
	Clothing	Street
	Width	1m
	Density	10% - 20% - 30%
	Reverse	Off
	Walk	On
Bicycle	Two lanes	Off
	Lane offset	0m
	Density	10% - 20% - 30%
	Speed	15 km/h
	Reverse	Off
Car	Lane count	1
	Two lanes	On
	Lane offset	0m
	Density	5% -15% -30%
	Speed	30 km/h
	Traffic rule	Right hand
	Reverse	Off

Materials

Used for	Name	Scale
Historic building - brick	Clean brick 08	4.00
Historic building - concrete	Poured concrete 03	6.00
Road	Asphalt 1	1.00
Bike Lane	Rubber red flooring	1.00
Pavement	Square cobblestone	1.00
Grass	Grass 4	2.00

Front Garden Vegetation

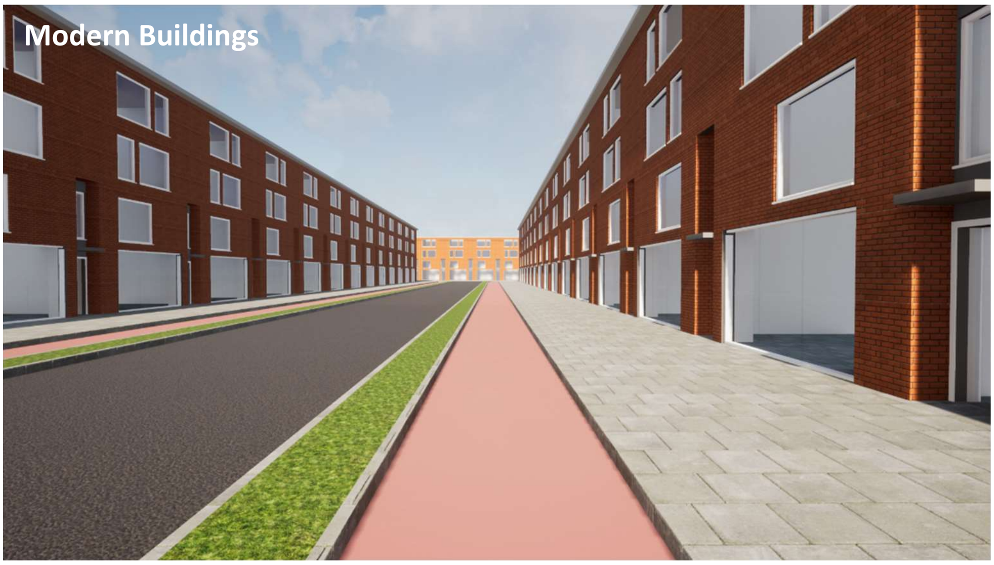
Used for	Name
Front Garden – 30 cm	Nasturtium 1
	Nasturtium 2
	Boston fern 1
Front Garden – 1.2 m	Gazania 2
	Leatherleaf fern 1
	Blue lupin 2
	Nasturtium 2
	RosaCanina 1
	RosaCanina 2

Video Settings

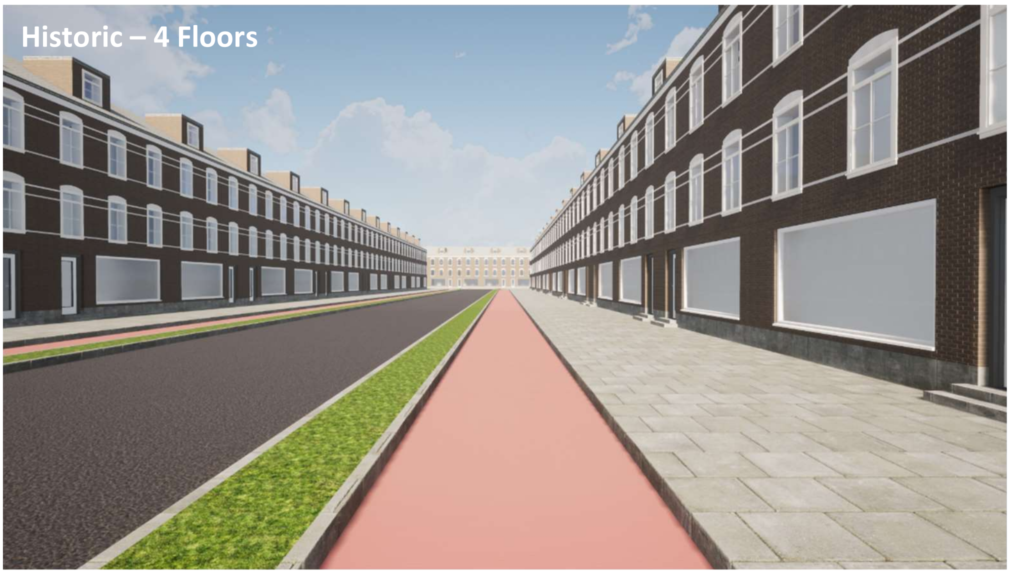
Type	Setting	Value
Location	Time	15 seconds
	Location	Amsterdam
	Time of Day	10:00
	Month	July
	North offset	170 degrees
	Background	None
Lighting	Exposure	0.00
	White balance	7300K
	GI	On
	Shadow	1000m
	Sun intensity	10
	Sun reflection	0.10
	Ambient	1.70
Weather	Season	Summer 100%
	Sun/rain	5th mark from left
	Growth	0.50
	Wind speed	1.00
	Direction	10 degrees
	Smog	0%
	Particles	Off
Camera	All settings	Default

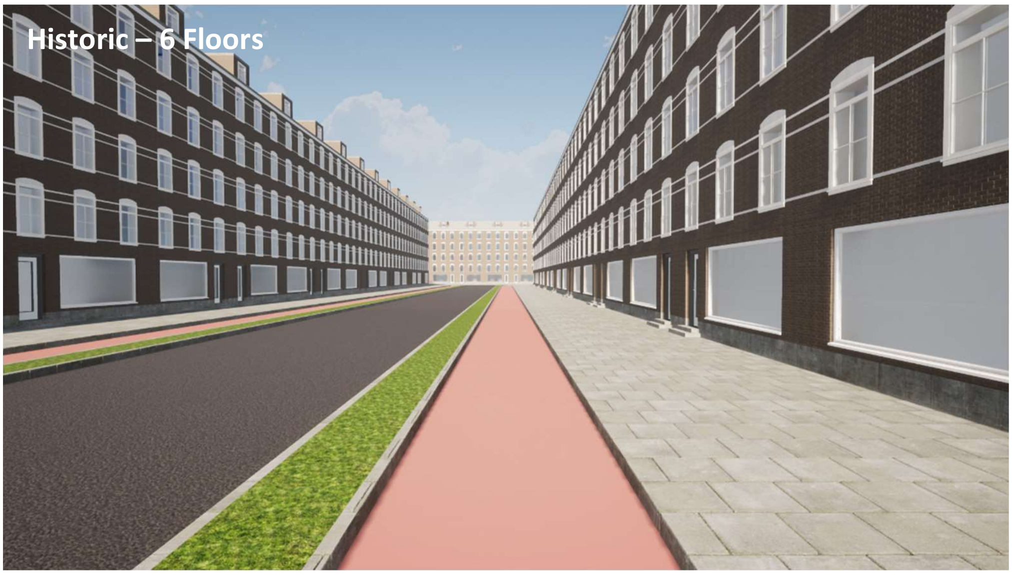
Appendix D – Visualized Attribute Levels

Building Type



Building Height






Modern – 2 Floors


Modern – 4 Floors


Modern – 6 Floors

Openness of Façade


Modern – Closed Façade


Modern – Semi-open Façade


Modern – Open Façade

Distance to Buildings

Front Garden

Activity of Ground Floor

Appendix E – Survey

Cycling to the train station

Welcome!

Thank you for taking part in this questionnaire about the influence of the presence of buildings on the route to a train station on the choice to cycle to a train station.
The purpose of this study is to gain insight in the preferences for certain aspects of the surroundings on the route from your home to a train station, with the aim to create design guidelines that encourage cycling to train stations as opposed to using the car.

This questionnaire is part of my graduation research at the Eindhoven University of Technology (TU/e). The results of this questionnaire are of importance for the success of my research.

The findings of this research will be anonymized and your data will be treated confidentially in accordance with the guidelines of the TU/e.

Filling out the survey will take 5 to 10 minutes and participation is voluntary. It is recommended to fill out the survey on a pc or tablet.

Machteld Sanders
Eindhoven University of Technology
m.f.d.sanders@student.tue.nl

There are 36 questions in this survey.

Part 1: Travel behavior

In this first part of the survey questions will be asked about your current travel behavior. These questions are asked to place the survey in the right context.

How often do you use the bicycle in general? *

❶ Choose one of the following answers
Please choose **only one** of the following:

- ◯ Very often
- ◯ Often
- ◯ Sometimes
- ◯ Seldom
- ◯ Never

What is the average distance you cycle per week? *

Only answer this question if the following conditions are met:
Answer was NOT 'Never' at question '1 [CTB7]' (How often do you use the bicycle in general?)

❶ Choose one of the following answers
Please choose **only one** of the following:

- ◯ 20 km or less per week
- ◯ 21-50 km per week
- ◯ 51-80 km per week
- ◯ More than 80 km per week

What type of bicycle do you most often use? *

Only answer this question if the following conditions are met:
Answer was NOT 'Never' at question '1 [CTB7]' (How often do you use the bicycle in general?)

❶ Choose one of the following answers
Please choose **only one** of the following:

- ◯ Standard bicycle
- ◯ Electric bicycle
- ◯ Other ____________

Do you have any reasons that can influence your experiences while cycling (physical disability/visual disability/etc.)? *

Only answer this question if the following conditions are met:
Answer was NOT 'Never' at question '1 [CTB7]' (How often do you use the bicycle in general?)

❶ Choose one of the following answers
Please choose **only one** of the following:

- ◯ Yes
- ◯ No

How often do you travel by train? *

❶ Choose one of the following answers
Please choose **only one** of the following:

- ◯ 4 or more times a week
- ◯ 1-3 times a week
- ◯ 1-3 times a month
- ◯ Less than once a month
- ◯ Never

When you travel by train, what is most often the purpose of your trip? *

Only answer this question if the following conditions are met:
Answer was NOT 'Never' at question '5 [CTB1]' (How often do you travel by train?)

❶ Choose one of the following answers
Please choose **only one** of the following:

- ◯ Work
- ◯ School
- ◯ Shopping
- ◯ Recreation
- ◯ Visiting friends and family
- ◯ Other ____________

How often do you cycle to the train station? *

Only answer this question if the following conditions are met:
Answer was NOT 'Never' at question '5 [CTB1]' (How often do you travel by train?) *and* Answer was NOT 'Never' at question '1 [CTB7]' (How often do you use the bicycle in general?)

❶ Choose one of the following answers
Please choose **only one** of the following:

- ◯ 4 or more times a week
- ◯ 1-3 times a week
- ◯ 1-3 times a month
- ◯ Less than once a month
- ◯ Never

If you currently never cycle to the train station, what is holding you back from cycling? *

Only answer this question if the following conditions are met:
Answer was 'Never' at question '7 [CTB3]' (How often do you cycle to the train station?)

❶ Choose one of the following answers
Please choose **only one** of the following:

- ◯ No availability of a bicycle
- ◯ Distance
- ◯ Lack of cycling facilities
- ◯ Unpleasant surroundings
- ◯ Disability
- ◯ Other

Part 2: Cycling route to the train station

In this part of the survey some questions are asked about **the cycling route** to the train station. For answering these questions, consider the usual cycling route from home to the train station. Even if you currently never cycle, please take the most common cycling route from your home to the train station in mind.

What is the travel distance from your home to the train station? *

Choose one of the following answers

Please choose **only one** of the following:

- ◯ Less than 5 km
- ◯ 5-10 km
- ◯ More than 10 km

Indicate to what extent you agree or disagree with the following statements.

Even if you currently never cycle, please take the most common cycling route from your home to the train station in mind.

On the cycling route to the train station...

*

Please choose the appropriate response for each item:

	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
...the buildings are mostly high-rise.	◯	◯	◯	◯	◯
...there is much variety in the buildings.	◯	◯	◯	◯	◯
...many buildings have open façades (many windows and doors).	◯	◯	◯	◯	◯
...there is much greenery.	◯	◯	◯	◯	◯
...there are many pedestrians.	◯	◯	◯	◯	◯
...there are many cyclists.	◯	◯	◯	◯	◯
...there are many cars.	◯	◯	◯	◯	◯

Part 3: Attitude towards cycling

Below several statements will be given about the attitude towards cycling.

Indicate how important the characteristics below are for you in your decison to cycle in general.

In the decision to cycle I find it important that...

*

Please choose the appropriate response for each item:

	Very unimportant	Unimportant	Neutral	Important	Very important
...it costs me little money.	○	○	○	○	○
...it saves me much time.	○	○	○	○	○
...it increases my health.	○	○	○	○	○
...the level of safety is high.	○	○	○	○	○
...the reliability is high.	○	○	○	○	○
...the surroundings are pleasant.	○	○	○	○	○
...the cycling facilities in my neighborhood are good.	○	○	○	○	○
...the distances to facilities (shops, school, work, etc.) are minor.	○	○	○	○	○

Part 4: Assessment of a bicycle environment - example question

This part of the survey will focus on your assessment of the environment of a bicycle route to a train station.

In each question you will be asked to watch a short video (15 seconds). Each video shows a virtual environment from the perspective of a cyclist. Aspects of the environment will differ in each video:

- The **distance** from the bicycle path to the buildings
- The presence of a **front garden**
- The **height** of the buildings
- The **openness** of the ground floor
- The building **types**
- The amount of **pedestrians, cyclists, and cars**

You will then be asked to assess the shown environment on four aspects:

- How much the environment stimulates you to cycle in general
- How much the environment stimulates you to cycle to the train station
- The attractiveness of the environment (how pleasant you find the environment for cycling)
- The bicycle-friendliness of the environment (how suitable you find the environment for cyclists)

It is strongly recommended to watch the videos on full screen for the best experience. If you want to watch the video again, you can click on the replay button in the bottom left corner.

You will first be given an example video.

The aspects of the environment that will differ in each video have the following values in the example video:

- The **distance** from the bicycle path to the buildings is **2 meters**.
- There is **small front garden** present.
- The **height** of the buildings is **4 floors**.
- The ground floor is **very open** (large windows).
- The building **types** are a **mix** of historical and modern buildings.
- There are **few pedestrians, cyclists, and cars** present.

Please click 'Next' to start the questions.

This part is repeated 6 times, with each time a different profile out of a pool of 18 profiles.

Part 4: Assessment of a bicycle environment

Please watch the video below by clicking on it.

Imagine your route to the train station looks like the environment shown in the video.

Distance: **2 meters** – Front garden: **no** – Height: **2 floors** – Openness: **closed** (small windows) – Types: **historic** buildings – Activity: **few** pedestrians, cyclists, and cars present.

It is strongly recommended to watch the videos on full screen for the best experience. If you want to watch the video again, you can click on the replay button in the bottom left corner.

Please answer the questions below on a scale from - - (to a very limited extent) to + + (to a very large extent).

*

Please choose the appropriate response for each item:

	- -	-	+/-	+	+ +
To what extent does the shown environment stimulate you to cycle in general?	○	○	○	○	○
To what extent does the shown environment stimulate you to cycle to the train station?	○	○	○	○	○
To what extent do you find the shown environment attractive?	○	○	○	○	○
To what extent do you find the shown environment bicycle-friendly?	○	○	○	○	○

- - = to a very limited extent

+ + = to a very large extent

Part 5: Personal information

Finally, you will be asked some questions regarding your person with the purpose of placing the survey in the right context. Your answers will be processed anonymously and cannot be traced back to a person or address.

What is your gender? *

❶ Choose one of the following answers
Please choose **only one** of the following:

- ◯ Male
- ◯ Female
- ◯ Other

What is your age? *

❶ Choose one of the following answers
Please choose **only one** of the following:

- ◯ Younger than 20 years
- ◯ 20-29 years
- ◯ 30-39 years
- ◯ 40-49 years
- ◯ 50-59 years
- ◯ 60-69 years
- ◯ 70 years or older

What is your education level? *

❶ Choose one of the following answers
Please choose **only one** of the following:

- ◯ Primary education
- ◯ Secondary General education
- ◯ Secondary Vocational education (NL: mbo)
- ◯ Higher professional education (NL: hbo)
- ◯ University education
- ◯ Other

What is your household composition? *

❶ Choose one of the following answers
Please choose **only one** of the following:

- ◯ Single (including living with roommates)
- ◯ Living at home with parents
- ◯ Single with children living at home
- ◯ With partner without children living at home
- ◯ With partner and with children living at home

What are the 4 digits of your postal code?

(This is asked to determine the degree of urbanization of the region you live in.)

*

Please write your answer here:

Outro

If you have any questions or remarks regarding the research or this survey, you can comment them below or send an email to m.f.d.sanders@student.tue.nl.

Please write your answer here:

This is the end of the survey.

If you have any questions or remarks regarding the research or this survey, you can send an email to m.f.d.sanders@student.tue.nl.

Thank you for participating!

Submit your survey.
Thank you for completing this survey.

Appendix F – Test of Parallel Lines

Cycling in General

Test of Parallel Lines[a]

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Null Hypothesis	424.133			
General	398.631	25.501	36	.904

The null hypothesis states that the location parameters (slope coefficients) are the same across response categories.

a. Link function: Logit.

Cycling to Train Station

Test of Parallel Lines[a]

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Null Hypothesis	435.371			
General	395.928	39.443	36	.319

The null hypothesis states that the location parameters (slope coefficients) are the same across response categories.

a. Link function: Logit.

Attractiveness

Test of Parallel Lines[a]

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Null Hypothesis	445.904			
General	408.077	37.827	36	.386

The null hypothesis states that the location parameters (slope coefficients) are the same across response categories.

a. Link function: Logit.

Bicycle-Suitability

Test of Parallel Lines[a]

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Null Hypothesis	468.805			
General	405.871	62.934	36	.004

The null hypothesis states that the location parameters (slope coefficients) are the same across response categories.

a. Link function: Logit.

Appendix G – Crosstab Analysis

Cycling-Variables

Case Processing Summary

	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
F_stim * F_stat	5364	100.0%	0	0.0%	5364	100.0%

F_stim * F_stat Crosstabulation

			F_stat					
			0	1	2	3	4	Total
F_stim	0	Count	210	64	72	23	4	373
		Expected Count	17.9	45.6	135.9	138.4	35.2	373.0
	1	Count	26	466	303	145	13	953
		Expected Count	45.7	116.5	347.3	353.6	89.9	953.0
	2	Count	11	107	1353	386	31	1888
		Expected Count	90.5	230.9	688.1	700.4	178.1	1888.0
	3	Count	5	16	208	1394	118	1741
		Expected Count	83.4	212.9	634.5	645.9	164.2	1741.0
	4	Count	5	3	19	42	340	409
		Expected Count	19.6	50.0	149.1	151.7	38.6	409.0
Total		Count	257	656	1955	1990	506	5364
		Expected Count	257.0	656.0	1955.0	1990.0	506.0	5364.0

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	8543.694[a]	16	.000
Likelihood Ratio	5562.686	16	.000
Linear-by-Linear Association	2948.387	1	.000
N of Valid Cases	5364		

a. 0 cells (,0%) have expected count less than 5. The minimum expected count is 17,87.

Symmetric Measures

		Value	Asymptotic Standard Error[a]	Approximate T[b]	Approximate Significance
Ordinal by Ordinal	Kendall's tau-b	.683	.009	70.690	.000
N of Valid Cases		5364			

a. Not assuming the null hypothesis.

b. Using the asymptotic standard error assuming the null hypothesis.

Experience-Variables

Case Processing Summary

	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
F_aantrek * F_vriend	5364	100.0%	0	0.0%	5364	100.0%

F_aantrek * F_vriend Crosstabulation

			F_vriend					Total
			0	1	2	3	4	
F_aantrek	0	Count	117	121	99	139	33	509
		Expected Count	14.2	52.7	121.4	242.0	78.8	509.0
	1	Count	24	336	436	582	92	1470
		Expected Count	41.1	152.1	350.5	698.8	227.5	1470.0
	2	Count	6	83	659	848	166	1762
		Expected Count	49.3	182.3	420.1	837.6	272.6	1762.0
	3	Count	3	15	83	951	247	1299
		Expected Count	36.3	134.4	309.7	617.5	201.0	1299.0
	4	Count	0	0	2	30	292	324
		Expected Count	9.1	33.5	77.3	154.0	50.1	324.0
Total		Count	150	555	1279	2550	830	5364
		Expected Count	150.0	555.0	1279.0	2550.0	830.0	5364.0

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	3401.275[a]	16	.000
Likelihood Ratio	2593.499	16	.000
Linear-by-Linear Association	1522.881	1	.000
N of Valid Cases	5364		

a. 0 cells (,0%) have expected count less than 5. The minimum expected count is 9,06.

Symmetric Measures

		Value	Asymptotic Standard Error[a]	Approximate T[b]	Approximate Significance
Ordinal by Ordinal	Kendall's tau-b	.452	.010	41.756	.000
N of Valid Cases		5364			

a. Not assuming the null hypothesis.

b. Using the asymptotic standard error assuming the null hypothesis.

Appendix H – Ordered Logit Model Output

Cycling in General

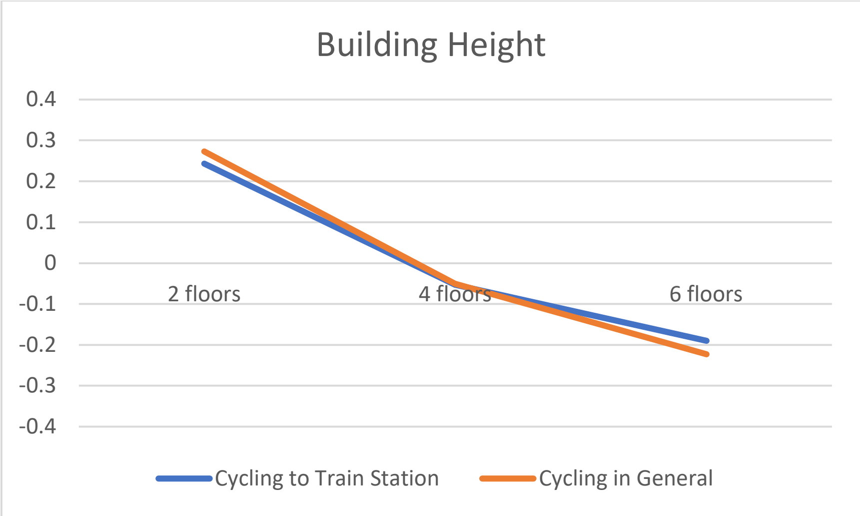
```
|-> ORDERED           ; Lhs = F_STIM
                      ; Rhs = ONE, HOOGTE1, HOOGTE2, TYPE1, TYPE2, OPEN1,
OPEN2, TUIN1, TUIN2, AFSTAND1, AFSTAND2, ACTIV1, ACTIV2
                      ; Logit$
Iterative procedure has converged
Normal exit:  21 iterations. Status=0, F=    .7481299D+04
+---------------------------------------------------------------------+
|                CELL FREQUENCIES FOR ORDERED CHOICES                  |
+---------------------------------------------------------------------+
|                Frequency         Cumulative  < =    Cumulative  > =  |
|Outcome       Count    Percent    Count    Percent   Count    Percent |
|------------ -------- ----------  -------- ----------  -------- ---------- |
|F_STIM=00       373     6.9538      373     6.9538    5364   100.0000 |
|F_STIM=01       953    17.7666     1326    24.7204    4991    93.0462 |
|F_STIM=02      1888    35.1976     3214    59.9180    4038    75.2796 |
|F_STIM=03      1740    32.4571     4954    92.3751    2150    40.0820 |
|F_STIM=04       409     7.6249     5364   100.0000     409     7.6249 |
+---------------------------------------------------------------------+
---------------------------------------------------------------------------
Ordered Probability Model
Dependent variable                F_STIM
Log likelihood function      -7481.29919
Restricted log likelihood    -7624.17603
Chi squared [ 12](P= .000)     285.75369
Significance level                .00000
McFadden Pseudo R-squared       .0187400
Estimation based on N =    5364, K =  16
Inf.Cr.AIC  =  14994.6 AIC/N =     2.795
Underlying probabilities based on Logistic
--------+------------------------------------------------------------------
        |                Standard            Prob.      95% Confidence
  F_STIM|  Coefficient     Error        z    |z|>Z*        Interval
--------+------------------------------------------------------------------
        |Index function for
probability.....................................
Constant|    2.66171***     .02929    90.87  .0000     2.60430    2.71912
 HOOGTE1|     .27312***     .03519     7.76  .0000      .20414     .34210
 HOOGTE2|    -.05057        .03512    -1.44  .1498     -.11940     .01826
   TYPE1|    -.02764        .03515     -.79  .4317     -.09652     .04125
   TYPE2|    -.13115***     .03504    -3.74  .0002     -.19983    -.06246
   OPEN1|    -.13371***     .03507    -3.81  .0001     -.20244    -.06497
   OPEN2|     .12300***     .03510     3.50  .0005      .05421     .19179
   TUIN1|    -.16832***     .03495    -4.82  .0000     -.23681    -.09982
   TUIN2|     .06534*       .03540     1.85  .0649     -.00404     .13472
AFSTAND1|    -.33890***     .03563    -9.51  .0000     -.40873    -.26908
AFSTAND2|     .03876        .03491     1.11  .2669     -.02966     .10717
  ACTIV1|     .15197***     .03533     4.30  .0000      .08271     .22122
  ACTIV2|     .10346***     .03502     2.95  .0031      .03482     .17209
        |Threshold parameters for
index.....................................
  Mu(01)|    1.51165***     .02903    52.07  .0000     1.45475    1.56855
  Mu(02)|    3.08623***     .03021   102.15  .0000     3.02701    3.14544
  Mu(03)|    5.24274***     .05219   100.46  .0000     5.14046    5.34503
--------+------------------------------------------------------------------
***, **, * ==>  Significance at 1%, 5%, 10% level.
---------------------------------------------------------------------------
```

Cycling to Train Station

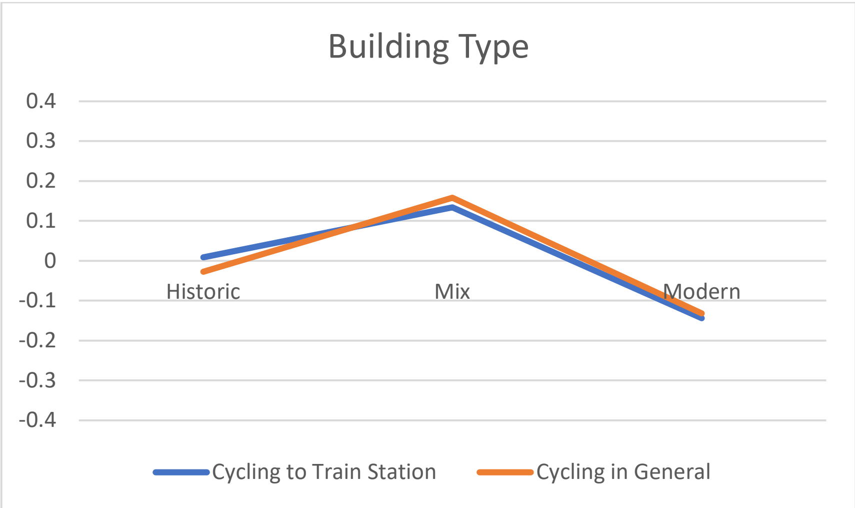
```
|-> ORDERED             ; Lhs = F_TRAIN
                        ; Rhs = ONE, HOOGTE1, HOOGTE2, TYPE1, TYPE2, OPEN1,
OPEN2, TUIN1, TUIN2, AFSTAND1, AFSTAND2, ACTIV1, ACTIV2
                        ; Logit$
Iterative procedure has converged
Normal exit:  21 iterations. Status=0, F=    .7178768D+04
+---------------------------------------------------------------------+
|                CELL FREQUENCIES FOR ORDERED CHOICES                 |
+---------------------------------------------------------------------+
|                Frequency         Cumulative  < =    Cumulative  > =  |
|Outcome       Count    Percent    Count    Percent    Count    Percent |
|------------ -------- ----------  -------- ----------  -------- ---------- |
|F_TRAIN=00      257     4.7912      257     4.7912      5364   100.0000 |
|F_TRAIN=01      656    12.2297      913    17.0209      5107    95.2088 |
|F_TRAIN=02     1955    36.4467     2868    53.4676      4451    82.9791 |
|F_TRAIN=03     1990    37.0992     4858    90.5667      2496    46.5324 |
|F_TRAIN=04      506     9.4333     5364   100.0000       506     9.4333 |
+---------------------------------------------------------------------+
---------------------------------------------------------------------------
Ordered Probability Model
Dependent variable              F_TRAIN
Log likelihood function     -7178.76783
Restricted log likelihood   -7300.40665
Chi squared [ 12](P= .000)    243.27763
Significance level               .00000
McFadden Pseudo R-squared      .0166619
Estimation based on N =   5364, K =  16
Inf.Cr.AIC  =  14389.5 AIC/N =    2.683
Underlying probabilities based on Logistic
--------+------------------------------------------------------------------
        |                 Standard            Prob.      95% Confidence
 F_TRAIN|  Coefficient      Error        z    |z|>Z*        Interval
--------+------------------------------------------------------------------
        |Index function for
probability......................................
Constant|    3.05563***      .03098    98.64  .0000     2.99491    3.11635
 HOOGTE1|     .24345***      .03559     6.84  .0000      .17370     .31320
 HOOGTE2|    -.05334         .03544    -1.51  .1323     -.12281     .01612
   TYPE1|     .00878         .03546      .25  .8045     -.06072     .07827
   TYPE2|    -.14346***      .03544    -4.05  .0001     -.21291    -.07401
   OPEN1|    -.11097***      .03537    -3.14  .0017     -.18028    -.04165
   OPEN2|     .10204***      .03556     2.87  .0041      .03234     .17174
   TUIN1|    -.13906***      .03523    -3.95  .0001     -.20812    -.07001
   TUIN2|     .06446*        .03578     1.80  .0716     -.00566     .13458
AFSTAND1|    -.33935***      .03596    -9.44  .0000     -.40982    -.26887
AFSTAND2|     .04854         .03529     1.38  .1691     -.02064     .11772
  ACTIV1|     .15229***      .03565     4.27  .0000      .08241     .22216
  ACTIV2|     .09490***      .03536     2.68  .0073      .02559     .16420
        |Threshold parameters for
index...........................................
  Mu(01)|    1.42671***      .03241    44.02  .0000     1.36319    1.49023
  Mu(02)|    3.20477***      .03131   102.36  .0000     3.14341    3.26614
  Mu(03)|    5.38566***      .04757   113.22  .0000     5.29243    5.47889
--------+------------------------------------------------------------------
***, **, * ==>  Significance at 1%, 5%, 10% level.
---------------------------------------------------------------------------
```

Appendix I – Graphs Part-Worth Utilities Cycling-Variables

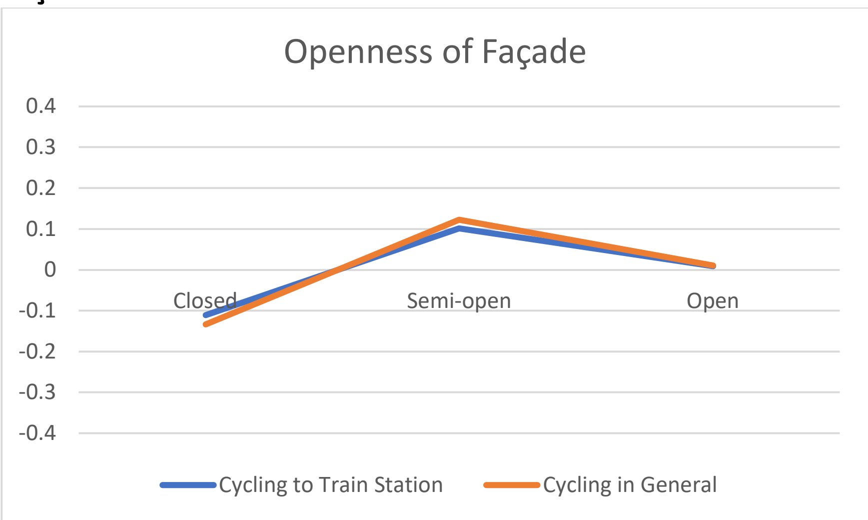
Building Height



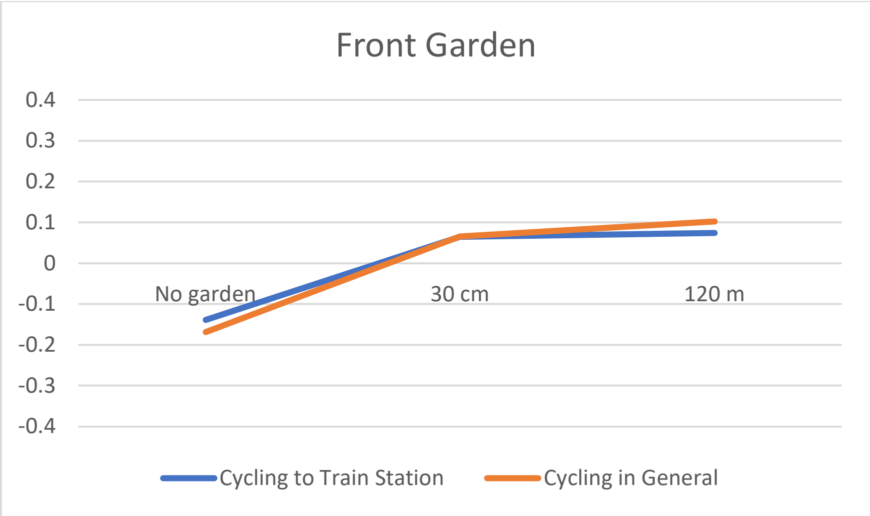
Building Type



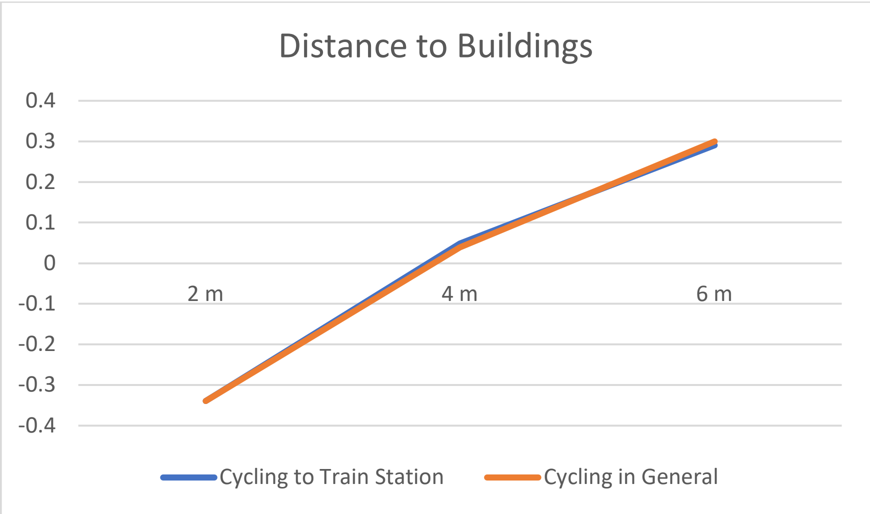
Openness of Façade



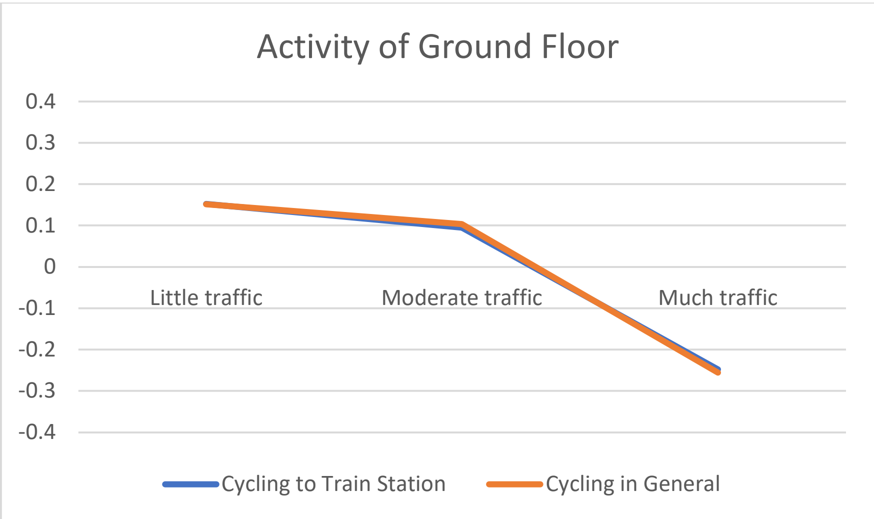
Front Garden



Distance to Buildings



Activity of Ground Floor



Appendix J – Random Effects Model Output

```
-----------------------------------------------------------------------------
Random Effects Ordered Probability Model
Dependent variable             F_TRAIN
Log likelihood function     -5381.23425
Restricted log likelihood   -7178.76783
Chi squared [   1](P= .000)  3595.06717
Significance level               .00000
(Cannot compute pseudo R2.  Use RHS=one
to obtain the required restricted logL)
Estimation based on N =   5364, K =  17
Inf.Cr.AIC  =  10796.5 AIC/N =    2.013
Underlying probabilities based on Logistic
Sample is  6 pds and   894 individuals.
--------+--------------------------------------------------------------------
        |                Standard            Prob.      95% Confidence
 F_TRAIN|  Coefficient      Error       z    |z|>Z*        Interval
--------+--------------------------------------------------------------------
        |Index function for probability......................................
Constant|     6.13322***      .13908    44.10  .0000     5.86062   6.40582
 HOOGTE1|      .49732***      .04347    11.44  .0000      .41212    .58252
 HOOGTE2|     -.09123*        .05057    -1.80  .0713     -.19035    .00790
   TYPE1|      .01580         .04639      .34  .7335     -.07512    .10671
   TYPE2|     -.20401***      .04887    -4.17  .0000     -.29979   -.10823
   OPEN1|     -.22547***      .04767    -4.73  .0000     -.31889   -.13204
   OPEN2|      .23994***      .04758     5.04  .0000      .14668    .33319
   TUIN1|     -.27797***      .04924    -5.65  .0000     -.37447   -.18147
   TUIN2|      .18450***      .05123     3.60  .0003      .08410    .28490
AFSTAND1|     -.71124***      .04512   -15.76  .0000     -.79968   -.62280
AFSTAND2|      .15334***      .05179     2.96  .0031      .05183    .25485
  ACTIV1|      .33214***      .04467     7.44  .0000      .24460    .41968
  ACTIV2|      .14473***      .05112     2.83  .0046      .04453    .24492
        |Threshold parameters for index model................................
  Mu(01)|     2.89934***      .08416    34.45  .0000     2.73439   3.06429
  Mu(02)|     6.41539***      .09840    65.20  .0000     6.22253   6.60826
  Mu(03)|     10.8142***      .12945    83.54  .0000     10.5605   11.0679
        |Std. Deviation of random effect.....................................
   Sigma|     3.09702***      .07559    40.97  .0000     2.94887   3.24517
--------+--------------------------------------------------------------------
***, **, * ==>  Significance at 1%, 5%, 10% level.
Model was estimated on Sep 17, 2021 at 08:10:26 PM
-----------------------------------------------------------------------------
```

Appendix K – Latent Class Model Output

```
-----------------------------------------------------------------------------
Latent Class / Panel OrdProbs Model
Dependent variable               F_TRAIN
Log likelihood function      -6057.75999
Estimation based on N =    5364, K =  33
Inf.Cr.AIC  =  12181.5 AIC/N =    2.271
Unbalanced panel has     894 individuals
Latent class model with 2 latent classes
Ordered probability model
Ordered LOGIT probability model
LHS variable = values 0,1,..., 4
--------+--------------------------------------------------------------------
        |                  Standard            Prob.      95% Confidence
 F_TRAIN|  Coefficient       Error       z    |z|>Z*         Interval
--------+--------------------------------------------------------------------
        |Model parameters for latent class
1..................................
Constant|    6.23179***      .46067    13.53  .0000     5.32890   7.13469
 HOOGTE1|     .43360***      .06158     7.04  .0000      .31291    .55429
 HOOGTE2|    -.12457*        .07039    -1.77  .0768     -.26254    .01340
   TYPE1|     .03703         .05953      .62  .5339     -.07964    .15370
   TYPE2|    -.09737         .06425    -1.52  .1296     -.22329    .02854
   OPEN1|    -.22162***      .06585    -3.37  .0008     -.35068   -.09256
   OPEN2|     .17773***      .06330     2.81  .0050      .05367    .30180
   TUIN1|    -.15693**       .06468    -2.43  .0153     -.28369   -.03017
   TUIN2|     .18358***      .06835     2.69  .0072      .04961    .31755
AFSTAND1|    -.66911***      .06293   -10.63  .0000     -.79246   -.54576
AFSTAND2|     .23521***      .07082     3.32  .0009      .09640    .37403
  ACTIV1|     .19650***      .06631     2.96  .0030      .06654    .32646
  ACTIV2|     .13381**       .06495     2.06  .0394      .00650    .26111
  Mu(01)|    2.82934***      .44104     6.42  .0000     1.96493   3.69376
  Mu(02)|    4.53127***      .45833     9.89  .0000     3.63296   5.42958
  Mu(03)|    7.84173***      .45977    17.06  .0000     6.94060   8.74285
        |Model parameters for latent class
2..................................
Constant|    2.40921***      .03396    70.94  .0000     2.34265   2.47578
 HOOGTE1|     .33549***      .05677     5.91  .0000      .22421    .44676
 HOOGTE2|    -.07513         .06064    -1.24  .2154     -.19399    .04373
   TYPE1|    -.03014         .05975     -.50  .6139     -.14725    .08696
   TYPE2|    -.18538***      .06076    -3.05  .0023     -.30447   -.06630
   OPEN1|    -.12171**       .05910    -2.06  .0394     -.23754   -.00588
   OPEN2|     .17253***      .06464     2.67  .0076      .04583    .29922
   TUIN1|    -.23397***      .06079    -3.85  .0001     -.35313   -.11482
   TUIN2|     .08873         .06580     1.35  .1775     -.04023    .21769
AFSTAND1|    -.37135***      .05624    -6.60  .0000     -.48159   -.26112
AFSTAND2|    -.05079         .06214     -.82  .4137     -.17258    .07100
  ACTIV1|     .22774***      .05893     3.86  .0001      .11223    .34325
  ACTIV2|     .06944         .06361     1.09  .2750     -.05523    .19410
  Mu(01)|    1.46839***      .03440    42.68  .0000     1.40097   1.53582
  Mu(02)|    4.50523***      .07089    63.56  .0000     4.36630   4.64417
  Mu(03)|    7.81051***      .29895    26.13  .0000     7.22457   8.39644
        |Estimated prior probabilities for class
membership..................
Class1Pr|     .48673***      .01812    26.87  .0000      .45122    .52224
Class2Pr|     .51327***      .01812    28.33  .0000      .47776    .54878
--------+--------------------------------------------------------------------
***, **, * ==>  Significance at 1%, 5%, 10% level.
Model was estimated on Sep 29, 2021 at 00:06:40 PM
-----------------------------------------------------------------------------
```

Appendix L – Multinomial Logistic Regression Model Output of Class Characteristics

Warnings

There are 393 (38.3%) cells (i.e., dependent variable levels by subpopulations) with zero frequencies.

Case Processing Summary

		N	Marginal Percentage
Class	Class 1	433	48.4%
	Class 2	461	51.6%
Gender_coded	Male	444	49.7%
	Female	450	50.3%
Edu_coded_new	Lower Education	200	22.4%
	Higher Education	694	77.6%
Bike_Type_new	Standard Bicycle	493	55.1%
	Electric Bicycle	294	32.9%
	Other (including never cycle)	107	12.0%
Distance_TS_new	Less than 5 km	556	62.2%
	More than 5 km	338	37.8%
StedGraad	ZeerHoogStedelijk	112	12.5%
	HoogStedelijk	255	28.5%
	Stedelijk	167	18.7%
	LaagStedelijk	169	18.9%
	NietStedelijk	191	21.4%
Age_coded_new	Younger than 40 years	129	14.4%
	40-59 years	491	54.9%
	60 years or older	274	30.6%
Cycle_Distance_new	20 km or less	480	53.7%
	More than 20 km	414	46.3%
HH_comp_new	Single (with or without children living at home)	184	20.6%
	With partner without children living at home	403	45.1%
	With partner and with children living at home	307	34.3%
Valid		894	100.0%
Missing		0	
Total		894	
Subpopulation		513[a]	

a. The dependent variable has only one value observed in 393 (76.6%) subpopulations.

Model Fitting Information

Model	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	903.091			
Final	872.894	30.197	14	.007

Goodness-of-Fit

	Chi-Square	df	Sig.
Pearson	508.186	498	.366
Deviance	670.452	498	.000

Pseudo R-Square

Cox and Snell	.033
Nagelkerke	.044
McFadden	.024

Likelihood Ratio Tests

Effect	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood of Reduced Model	Chi-Square	df	Sig.
Intercept	872.894[a]	.000	0	.
Gender_coded	878.536	5.642	1	.018
Edu_coded_new	879.447	6.554	1	.010
Bike_Type_new	873.367	.473	2	.789
Distance_TS_new	878.150	5.257	1	.022
StedGraad	877.116	4.223	4	.377
Age_coded_new	875.137	2.244	2	.326
Cycle_Distance_new	878.547	5.654	1	.017
HH_comp_new	874.022	1.129	2	.569

The chi-square statistic is the difference in -2 log-likelihoods between the final model and a reduced model. The reduced model is formed by omitting an effect from the final model. The null hypothesis is that all parameters of that effect are 0.

a. This reduced model is equivalent to the final model because omitting the effect does not increase the degrees of freedom.

Parameter Estimates

Class[a]		B	Std. Error	Wald	df	Sig.	Exp(B)	95% Confidence Interval for Exp(B) Lower Bound	Upper Bound
Class 1	Intercept	.353	.339	1.084	1	.298			
	[Gender_coded=1]	-.339	.143	5.611	1	.018	.712	.538	.943
	[Gender_coded=2]	0[b]	.	.	0	.	.	.	.
	[Edu_coded_new=1,00]	-.431	.169	6.468	1	.011	.650	.466	.906
	[Edu_coded_new=2,00]	0[b]	.	.	0	.	.	.	.
	[Bike_Type_new=1,00]	.141	.222	.405	1	.524	1.152	.746	1.779
	[Bike_Type_new=2,00]	.154	.238	.422	1	.516	1.167	.733	1.859
	[Bike_Type_new=3,00]	0[b]	.	.	0	.	.	.	.
	[Distance_TS_new=1,00]	.358	.157	5.216	1	.022	1.431	1.052	1.947
	[Distance_TS_new=2,00]	0[b]	.	.	0	.	.	.	.
	[StedGraad=1]	-.069	.262	.069	1	.793	.933	.558	1.561
	[StedGraad=2]	-.077	.211	.135	1	.713	.925	.612	1.399
	[StedGraad=3]	-.364	.237	2.348	1	.125	.695	.437	1.107
	[StedGraad=4]	-.321	.227	1.998	1	.157	.725	.465	1.132
	[StedGraad=5]	0[b]	.	.	0	.	.	.	.
	[Age_coded_new=1,00]	.156	.233	.447	1	.504	1.169	.740	1.845
	[Age_coded_new=2,00]	-.138	.173	.635	1	.425	.871	.621	1.223
	[Age_coded_new=3,00]	0[b]	.	.	0	.	.	.	.
	[Cycle_Distance_new=1,00]	-.346	.146	5.625	1	.018	.708	.532	.942
	[Cycle_Distance_new=2,00]	0[b]	.	.	0	.	.	.	.
	[HH_comp_new=1,00]	-.183	.198	.856	1	.355	.832	.564	1.228
	[HH_comp_new=2,00]	-.154	.170	.821	1	.365	.857	.614	1.196
	[HH_comp_new=3,00]	0[b]	.	.	0	.	.	.	.

a. The reference category is: Class 2.

b. This parameter is set to zero because it is redundant.

Appendix M – Multinomial Logistic Regression Model Output of Experience-Variables

Attractiveness

Case Processing Summary

		N	Marginal Percentage
F_aantrek	0	509	9.5%
	1	1470	27.4%
	2	1762	32.8%
	3	1299	24.2%
	4	324	6.0%
Valid		5364	100.0%
Missing		0	
Total		5364	
Subpopulation		18	

Model Fitting Information

	Model Fitting Criteria	Likelihood Ratio Tests		
Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	966.634			
Final	406.933	559.701	48	.000

Goodness-of-Fit

	Chi-Square	df	Sig.
Pearson	34.210	20	.025
Deviance	34.222	20	.025

Pseudo R-Square

Cox and Snell	.099
Nagelkerke	.105
McFadden	.036

Likelihood Ratio Tests

Effect	Model Fitting Criteria: -2 Log Likelihood of Reduced Model	Likelihood Ratio Tests: Chi-Square	df	Sig.
Intercept	2090.419	1683.486	4	.000
Hoogte1	502.225	95.292	4	.000
Hoogte2	413.265	6.332	4	.176
Type1	408.261	1.328	4	.857
Type2	460.497	53.565	4	.000
Openheid1	434.993	28.060	4	.000
Openheid2	421.581	14.648	4	.005
Voortuin1	474.489	67.556	4	.000
Voortuin2	410.545	3.612	4	.461
Afstand1	511.654	104.721	4	.000
Afstand2	412.293	5.360	4	.252
Activiteit1	424.726	17.793	4	.001
Activiteit2	431.365	24.432	4	.000

The chi-square statistic is the difference in -2 log-likelihoods between the final model and a reduced model. The reduced model is formed by omitting an effect from the final model. The null hypothesis is that all parameters of that effect are 0.

Parameter Estimates

F_aantrek[a]		B	Std. Error	Wald	df	Sig.	Exp(B)	95% Confidence Interval for Exp(B): Lower Bound	95% Confidence Interval for Exp(B): Upper Bound
0	Intercept	-1.333	.055	595.080	1	.000			
	Hoogte1	-.152	.082	3.402	1	.065	.859	.731	1.010
	Hoogte2	-.151	.077	3.862	1	.049	.860	.740	1.000
	Type1	-.002	.075	.000	1	.982	.998	.861	1.157
	Type2	.103	.071	2.103	1	.147	1.109	.964	1.275
	Openheid1	.167	.073	5.254	1	.022	1.182	1.025	1.364
	Openheid2	-.183	.079	5.345	1	.021	.833	.713	.973
	Voortuin1	.118	.073	2.618	1	.106	1.125	.975	1.298
	Voortuin2	-.108	.077	1.979	1	.160	.898	.772	1.043
	Afstand1	.361	.072	25.346	1	.000	1.435	1.247	1.652
	Afstand2	-.075	.074	1.037	1	.309	.927	.802	1.072
	Activiteit1	-.031	.076	.162	1	.687	.970	.836	1.125

	Activiteit2	-.219	.078	7.970	1	.005	.803	.690	.935
1	Intercept	-.212	.036	34.000	1	.000			
	Hoogte1	-.119	.054	4.870	1	.027	.888	.799	.987
	Hoogte2	-.017	.050	.109	1	.741	.984	.891	1.085
	Type1	.044	.051	.775	1	.379	1.045	.947	1.154
	Type2	.036	.050	.534	1	.465	1.037	.941	1.143
	Openheid1	.112	.050	5.094	1	.024	1.119	1.015	1.234
	Openheid2	-.090	.052	2.945	1	.086	.914	.825	1.013
	Voortuin1	.095	.049	3.717	1	.054	1.100	.998	1.212
	Voortuin2	-.043	.051	.715	1	.398	.958	.867	1.058
	Afstand1	.219	.050	18.872	1	.000	1.245	1.128	1.374
	Afstand2	-.057	.050	1.263	1	.261	.945	.856	1.043
	Activiteit1	-.086	.052	2.723	1	.099	.918	.829	1.016
	Activiteit2	-.058	.051	1.307	1	.253	.944	.854	1.042
3	Intercept	-.369	.038	92.509	1	.000			
	Hoogte1	.320	.053	36.595	1	.000	1.378	1.242	1.528
	Hoogte2	-.075	.053	1.985	1	.159	.928	.836	1.030
	Type1	.024	.053	.200	1	.655	1.024	.923	1.137
	Type2	-.259	.054	22.677	1	.000	.772	.694	.859
	Openheid1	-.109	.054	4.068	1	.044	.897	.806	.997
	Openheid2	.049	.054	.816	1	.366	1.050	.945	1.167
	Voortuin1	-.303	.055	30.614	1	.000	.739	.664	.822
	Voortuin2	.019	.053	.120	1	.729	1.019	.917	1.131
	Afstand1	-.234	.057	16.903	1	.000	.791	.708	.885
	Afstand2	.048	.052	.853	1	.356	1.050	.947	1.163
	Activiteit1	.143	.053	7.238	1	.007	1.154	1.040	1.281
	Activiteit2	.072	.053	1.889	1	.169	1.075	.970	1.192
4	Intercept	-1.903	.072	697.877	1	.000			
	Hoogte1	.495	.094	27.795	1	.000	1.641	1.365	1.973
	Hoogte2	-.142	.099	2.038	1	.153	.868	.714	1.054
	Type1	.080	.095	.702	1	.402	1.083	.899	1.305
	Type2	-.426	.100	18.226	1	.000	.653	.537	.794
	Openheid1	-.234	.103	5.179	1	.023	.791	.646	.968
	Openheid2	.151	.097	2.434	1	.119	1.163	.962	1.405
	Voortuin1	-.314	.101	9.760	1	.002	.730	.600	.890
	Voortuin2	-.079	.102	.609	1	.435	.924	.757	1.127
	Afstand1	-.356	.109	10.642	1	.001	.700	.565	.867
	Afstand2	-.088	.096	.838	1	.360	.916	.758	1.106
	Activiteit1	.107	.093	1.329	1	.249	1.113	.928	1.335
	Activiteit2	.259	.093	7.789	1	.005	1.296	1.080	1.555

a. The reference category is: 2.

Bicycle-Suitability

Warnings

There are 1 (1,1%) cells (i.e., dependent variable levels by subpopulations) with zero frequencies.

Case Processing Summary

		N	Marginal Percentage
F_vriend	0	150	2.8%
	1	555	10.3%
	2	1279	23.8%
	3	2550	47.5%
	4	830	15.5%
Valid		5364	100.0%
Missing		0	
Total		5364	
Subpopulation		18	

Model Fitting Information

	Model Fitting Criteria	Likelihood Ratio Tests		
Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	972.773			
Final	402.339	570.434	48	.000

Goodness-of-Fit

	Chi-Square	df	Sig.
Pearson	48.967	20	.000
Deviance	50.723	20	.000

Pseudo R-Square

Cox and Snell	.101
Nagelkerke	.109
McFadden	.040

Likelihood Ratio Tests

Effect	Model Fitting Criteria -2 Log Likelihood of Reduced Model	Likelihood Ratio Tests Chi-Square	df	Sig.
Intercept	3548.607	3146.268	4	.000
Hoogte1	450.051	47.712	4	.000
Hoogte2	412.775	10.436	4	.034
Type1	414.038	11.699	4	.020
Type2	414.108	11.769	4	.019
Openheid1	410.251	7.912	4	.095
Openheid2	414.934	12.595	4	.013
Voortuin1	406.972	4.633	4	.327
Voortuin2	409.536	7.197	4	.126
Afstand1	639.015	236.676	4	.000
Afstand2	426.999	24.660	4	.000
Activiteit1	467.288	64.949	4	.000
Activiteit2	413.038	10.699	4	.030

The chi-square statistic is the difference in -2 log-likelihoods between the final model and a reduced model. The reduced model is formed by omitting an effect from the final model. The null hypothesis is that all parameters of that effect are 0.

Parameter Estimates

F_vriend[a]		B	Std. Error	Wald	df	Sig.	Exp(B)	95% Confidence Interval for Exp(B) Lower Bound	95% Confidence Interval for Exp(B) Upper Bound
0	Intercept	-2.362	.103	526.560	1	.000			
	Hoogte1	-.065	.147	.194	1	.660	.937	.702	1.251
	Hoogte2	-.104	.145	.519	1	.471	.901	.678	1.197
	Type1	-.188	.142	1.766	1	.184	.828	.628	1.094
	Type2	.108	.131	.683	1	.409	1.114	.862	1.439
	Openheid1	.120	.135	.790	1	.374	1.128	.865	1.469
	Openheid2	-.305	.146	4.374	1	.036	.737	.554	.981
	Voortuin1	-.135	.142	.903	1	.342	.874	.661	1.154
	Voortuin2	-.247	.148	2.787	1	.095	.781	.584	1.044
	Afstand1	.453	.125	13.210	1	.000	1.573	1.232	2.009
	Afstand2	-.103	.144	.514	1	.473	.902	.681	1.196
	Activiteit1	-.118	.147	.646	1	.421	.888	.666	1.185

	Activiteit2	-.174	.147	1.401	1	.237	.840	.629	1.121
1	Intercept	-1.012	.058	303.422	1	.000			
	Hoogte1	-.251	.085	8.716	1	.003	.778	.658	.919
	Hoogte2	.165	.077	4.579	1	.032	1.179	1.014	1.372
	Type1	-.247	.081	9.330	1	.002	.781	.667	.915
	Type2	.159	.075	4.517	1	.034	1.172	1.012	1.358
	Openheid1	.043	.077	.305	1	.581	1.044	.897	1.214
	Openheid2	-.142	.081	3.030	1	.082	.868	.740	1.018
	Voortuin1	-.005	.077	.004	1	.952	.995	.855	1.158
	Voortuin2	-.135	.081	2.733	1	.098	.874	.745	1.025
	Afstand1	.378	.074	26.111	1	.000	1.459	1.262	1.687
	Afstand2	-.080	.080	.979	1	.322	.923	.789	1.081
	Activiteit1	-.284	.086	10.916	1	.001	.753	.636	.891
	Activiteit2	-.076	.081	.887	1	.346	.926	.790	1.086
3	Intercept	.687	.035	386.226	1	.000			
	Hoogte1	.094	.050	3.607	1	.058	1.099	.997	1.211
	Hoogte2	-.053	.049	1.176	1	.278	.948	.862	1.044
	Type1	-.040	.048	.675	1	.411	.961	.874	1.057
	Type2	-.014	.049	.075	1	.784	.987	.896	1.087
	Openheid1	-.076	.049	2.450	1	.118	.927	.843	1.019
	Openheid2	.048	.050	.953	1	.329	1.050	.952	1.157
	Voortuin1	-.061	.049	1.578	1	.209	.941	.855	1.035
	Voortuin2	.016	.049	.112	1	.738	1.016	.924	1.119
	Afstand1	-.419	.049	72.245	1	.000	.658	.597	.725
	Afstand2	.182	.049	13.886	1	.000	1.200	1.090	1.321
	Activiteit1	.220	.050	19.420	1	.000	1.246	1.130	1.374
	Activiteit2	.011	.049	.053	1	.818	1.011	.919	1.113
4	Intercept	-.507	.048	111.943	1	.000			
	Hoogte1	.315	.065	23.656	1	.000	1.370	1.207	1.555
	Hoogte2	-.067	.066	1.028	1	.311	.935	.821	1.065
	Type1	.003	.065	.002	1	.961	1.003	.883	1.140
	Type2	-.117	.066	3.137	1	.077	.889	.781	1.013
	Openheid1	-.123	.066	3.475	1	.062	.884	.777	1.006
	Openheid2	.060	.066	.812	1	.368	1.061	.932	1.208
	Voortuin1	-.124	.065	3.622	1	.057	.883	.777	1.004
	Voortuin2	.020	.066	.095	1	.758	1.021	.896	1.162
	Afstand1	-.604	.072	69.559	1	.000	.546	.474	.630
	Afstand2	.144	.066	4.824	1	.028	1.155	1.016	1.314
	Activiteit1	.285	.065	19.062	1	.000	1.330	1.170	1.511
	Activiteit2	.151	.065	5.431	1	.020	1.163	1.024	1.320

a. The reference category is: 2.

Appendix N – Linear Regression Model Output

Cycling-Variables

Cronbach's α

Case Processing Summary

		N	%
Cases	Valid	5364	100.0
	Excluded[a]	0	.0
	Total	5364	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.851	.852	2

Item Statistics

	Mean	Std. Deviation	N
F_stim	2.16	1.030	5364
F_stat	2.34	.973	5364

Inter-Item Correlation Matrix

	F_stim	F_stat
F_stim	1.000	.741
F_stat	.741	1.000

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
F_stim	2.34	.946	.741	.550	.
F_stat	2.16	1.060	.741	.550	.

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
4.50	3.490	1.868	2

Linear Regression Output

Correlations		F_cycle	Hoog1	Hoog2	Type1	Type2	Open1	Open2	Tuin1	Tuin2	Afst1	Afst2	Activ1	Activ2
Pearson Correlation	F_cycle	1.000	.106	.036	-.031	-.059	-.032	.024	-.054	-.005	-.147	-.058	.085	.082
	Hoogte1	.106	1.000	.496	-.012	.015	.010	.009	-.005	-.013	.001	.014	-.012	-.011
	Hoogte2	.036	.496	1.000	-.007	-.003	-.005	-.015	.002	-.008	-.004	-.001	-.009	-.006
	Type1	-.031	-.012	-.007	1.000	.499	.019	.014	-.004	-.017	-.004	-.004	.007	-.005
	Type2	-.059	.015	-.003	.499	1.000	.015	.016	-.005	-.017	-.006	.013	.000	.009
	Openheid1	-.032	.010	-.005	.019	.015	1.000	.497	-.001	.000	.014	.002	-.010	-.006
	Openheid2	.024	.009	-.015	.014	.016	.497	1.000	-.015	-.014	.008	.008	-.008	.018
	Voortuin1	-.054	-.005	.002	-.004	-.005	-.001	-.015	1.000	.504	.003	-.007	-.001	-.008
	Voortuin2	-.005	-.013	-.008	-.017	-.017	.000	-.014	.504	1.000	-.008	-.016	-.010	-.018
	Afstand1	-.147	.001	-.004	-.004	-.006	.014	.008	.003	-.008	1.000	.504	.006	.000
	Afstand2	-.058	.014	-.001	-.004	.013	.002	.008	-.007	-.016	.504	1.000	.002	.014
	Activiteit1	.085	-.012	-.009	.007	.000	-.010	-.008	-.001	-.010	.006	.002	1.000	.500
	Activiteit2	.082	-.011	-.006	-.005	.009	-.006	.018	-.008	-.018	.000	.014	.500	1.000
Sig. (1-tailed)	F_cycle	.	.000	.004	.011	.000	.009	.039	.000	.370	.000	.000	.000	.000
	Hoogte1	.000	.	.000	.184	.141	.239	.244	.348	.171	.477	.148	.190	.218
	Hoogte2	.004	.000	.	.303	.410	.348	.137	.451	.289	.379	.475	.248	.333
	Type1	.011	.184	.303	.	.000	.088	.147	.372	.112	.386	.373	.296	.364
	Type2	.000	.141	.410	.000	.	.131	.126	.357	.110	.343	.171	.499	.251
	Openheid1	.009	.239	.348	.088	.131	.	.000	.475	.486	.154	.453	.230	.319
	Openheid2	.039	.244	.137	.147	.126	.000	.	.131	.147	.280	.285	.283	.099
	Voortuin1	.000	.348	.451	.372	.357	.475	.131	.	.000	.400	.306	.460	.278
	Voortuin2	.370	.171	.289	.112	.110	.486	.147	.000	.	.273	.120	.234	.088
	Afstand1	.000	.477	.379	.386	.343	.154	.280	.400	.273	.	.000	.319	.498
	Afstand2	.000	.148	.475	.373	.171	.453	.285	.306	.120	.000	.	.450	.161
	Activiteit1	.000	.190	.248	.296	.499	.230	.283	.460	.234	.319	.450	.	.000
	Activiteit2	.000	.218	.333	.364	.251	.319	.099	.278	.088	.498	.161	.000	.
N	F_cycle	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364
	Hoogte1	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364
	Hoogte2	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364
	Type1	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364
	Type2	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364
	Openheid1	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364
	Openheid2	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364
	Voortuin1	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364
	Voortuin2	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364
	Afstand1	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364
	Afstand2	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364
	Activiteit1	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364
	Activiteit2	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.231[a]	.053	.051	.90997

a. Predictors: (Constant), Activiteit2, Afstand1, Type1, Voortuin1, Hoogte2, Openheid1, Hoogte1, Openheid2, Type2, Activiteit1, Voortuin2, Afstand2

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	248.860	12	20.738	25.045	.000[b]
	Residual	4430.885	5351	.828		
	Total	4679.745	5363			

a. Dependent Variable: F_cycle

b. Predictors: (Constant), Activiteit2, Afstand1, Type1, Voortuin1, Hoogte2, Openheid1, Hoogte1, Openheid2, Type2, Activiteit1, Voortuin2, Afstand2

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	2.248	.012		180.785	.000
	Hoogte1	.135	.018	.118	7.713	.000
	Hoogte2	-.024	.018	-.021	-1.389	.165
	Type1	.001	.018	.001	.063	.950
	Type2	-.072	.018	-.063	-4.076	.000
	Openheid1	-.063	.018	-.055	-3.577	.000
	Openheid2	.058	.018	.051	3.317	.001
	Voortuin1	-.077	.017	-.068	-4.407	.000
	Voortuin2	.036	.018	.031	2.029	.043
	Afstand1	-.180	.018	-.156	-10.134	.000
	Afstand2	.021	.017	.019	1.221	.222
	Activiteit1	.071	.018	.062	4.027	.000
	Activiteit2	.059	.018	.051	3.334	.001

a. Dependent Variable: F_cycle

Experience-Variables

Cronbach's α

Case Processing Summary

		N	%
Cases	Valid	5364	100.0
	Excluded[a]	0	.0
	Total	5364	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.693	.695	2

Item Statistics

	Mean	Std. Deviation	N
F_aantrek	1.90	1.062	5364
F_vriend	2.63	.958	5364

Inter-Item Correlation Matrix

	F_aantrek	F_vriend
F_aantrek	1.000	.533
F_vriend	.533	1.000

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
F_aantrek	2.63	.919	.533	.284	.
F_vriend	1.90	1.127	.533	.284	.

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
4.52	3.131	1.769	2

Linear Regression Output

Correlations		F_exper	Hoog1	Hoog2	Type1	Type2	Open1	Open2	Tuin1	Tuin2	Afst1	Afst2	Activ1	Activ2
Pearson Correlation	F_exper	1.000	.144	.056	-.024	-.078	-.042	.034	-.065	-.002	-.208	-.059	.137	.121
	Hoogte1	.144	1.000	.496	-.012	.015	.010	.009	-.005	-.013	.001	.014	-.012	-.011
	Hoogte2	.056	.496	1.000	-.007	-.003	-.005	-.015	.002	-.008	-.004	-.001	-.009	-.006
	Type1	-.024	-.012	-.007	1.000	.499	.019	.014	-.004	-.017	-.004	-.004	.007	-.005
	Type2	-.078	.015	-.003	.499	1.000	.015	.016	-.005	-.017	-.006	.013	.000	.009
	Openheid1	-.042	.010	-.005	.019	.015	1.000	.497	-.001	.000	.014	.002	-.010	-.006
	Openheid2	.034	.009	-.015	.014	.016	.497	1.000	-.015	-.014	.008	.008	-.008	.018
	Voortuin1	-.065	-.005	.002	-.004	-.005	-.001	-.015	1.000	.504	.003	-.007	-.001	-.008
	Voortuin2	-.002	-.013	-.008	-.017	-.017	.000	-.014	.504	1.000	-.008	-.016	-.010	-.018
	Afstand1	-.208	.001	-.004	-.004	-.006	.014	.008	.003	-.008	1.000	.504	.006	.000
	Afstand2	-.059	.014	-.001	-.004	.013	.002	.008	-.007	-.016	.504	1.000	.002	.014
	Activiteit1	.137	-.012	-.009	.007	.000	-.010	-.008	-.001	-.010	.006	.002	1.000	.500
	Activiteit2	.121	-.011	-.006	-.005	.009	-.006	.018	-.008	-.018	.000	.014	.500	1.000
Sig. (1-tailed)	F_exper	.	.000	.000	.037	.000	.001	.006	.000	.446	.000	.000	.000	.000
	Hoogte1	.000	.	.000	.184	.141	.239	.244	.348	.171	.477	.148	.190	.218
	Hoogte2	.000	.000	.	.303	.410	.348	.137	.451	.289	.379	.475	.248	.333
	Type1	.037	.184	.303	.	.000	.088	.147	.372	.112	.386	.373	.296	.364
	Type2	.000	.141	.410	.000	.	.131	.126	.357	.110	.343	.171	.499	.251
	Openheid1	.001	.239	.348	.088	.131	.	.000	.475	.486	.154	.453	.230	.319
	Openheid2	.006	.244	.137	.147	.126	.000	.	.131	.147	.280	.285	.283	.099
	Voortuin1	.000	.348	.451	.372	.357	.475	.131	.	.000	.400	.306	.460	.278
	Voortuin2	.446	.171	.289	.112	.110	.486	.147	.000	.	.273	.120	.234	.088
	Afstand1	.000	.477	.379	.386	.343	.154	.280	.400	.273	.	.000	.319	.498
	Afstand2	.000	.148	.475	.373	.171	.453	.285	.306	.120	.000	.	.450	.161
	Activiteit1	.000	.190	.248	.296	.499	.230	.283	.460	.234	.319	.450	.	.000
	Activiteit2	.000	.218	.333	.364	.251	.319	.099	.278	.088	.498	.161	.000	.
N	F_exper	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364
	Hoogte1	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364
	Hoogte2	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364
	Type1	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364
	Type2	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364
	Openheid1	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364
	Openheid2	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364
	Voortuin1	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364
	Voortuin2	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364
	Afstand1	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364
	Afstand2	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364
	Activiteit1	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364
	Activiteit2	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.328[a]	.108	.106	.83657

a. Predictors: (Constant), Activiteit2, Afstand1, Type1, Voortuin1, Hoogte2, Openheid1, Hoogte1, Openheid2, Type2, Activiteit1, Voortuin2, Afstand2

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	452.532	12	37.711	53.884	.000[b]
	Residual	3744.906	5351	.700		
	Total	4197.438	5363			

a. Dependent Variable: F_exper

b. Predictors: (Constant), Activiteit2, Afstand1, Type1, Voortuin1, Hoogte2, Openheid1, Hoogte1, Openheid2, Type2, Activiteit1, Voortuin2, Afstand2

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	2.258	.011		197.518	.000
	Hoogte1	.170	.016	.157	10.576	.000
	Hoogte2	-.022	.016	-.020	-1.368	.171
	Type1	.026	.016	.024	1.612	.107
	Type2	-.102	.016	-.094	-6.332	.000
	Openheid1	-.078	.016	-.072	-4.863	.000
	Openheid2	.076	.016	.070	4.680	.000
	Voortuin1	-.089	.016	-.083	-5.524	.000
	Voortuin2	.046	.016	.043	2.854	.004
	Afstand1	-.260	.016	-.238	-15.902	.000
	Afstand2	.062	.016	.058	3.880	.000
	Activiteit1	.115	.016	.106	7.084	.000
	Activiteit2	.074	.016	.069	4.595	.000

a. Dependent Variable: F_exper

Combination of the Four Dependent Variables

Cronbach's α

Case Processing Summary

		N	%
Cases	Valid	5364	100.0
	Excluded[a]	0	.0
	Total	5364	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.868	.868	4

Item Statistics

	Mean	Std. Deviation	N
F_stim	2.16	1.030	5364
F_stat	2.34	.973	5364
F_aantrek	1.90	1.062	5364
F_vriend	2.63	.958	5364

Inter-Item Correlation Matrix

	F_stim	F_stat	F_aantrek	F_vriend
F_stim	1.000	.741	.704	.560
F_stat	.741	1.000	.590	.598
F_aantrek	.704	.590	1.000	.533
F_vriend	.560	.598	.533	1.000

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
F_stim	6.87	6.411	.792	.661	.800
F_stat	6.68	6.833	.751	.601	.818
F_aantrek	7.13	6.628	.703	.526	.838
F_vriend	6.40	7.375	.635	.413	.863

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
9.03	11.598	3.406	4

Linear Regression Output

Correlations		F_Combi	Hoog1	Hoog2	Type1	Type2	Open1	Open2	Tuin1	Tuin2	Afst1	Afst2	Activ1	Activ2
Pearson Correlation	F_Combi	1.000	.133	.049	-.030	-.073	-.039	.031	-.063	-.003	-.189	-.063	.118	.108
	Hoogte1	.133	1.000	.496	-.012	.015	.010	.009	-.005	-.013	.001	.014	-.012	-.011
	Hoogte2	.049	.496	1.000	-.007	-.003	-.005	-.015	.002	-.008	-.004	-.001	-.009	-.006
	Type1	-.030	-.012	-.007	1.000	.499	.019	.014	-.004	-.017	-.004	-.004	.007	-.005
	Type2	-.073	.015	-.003	.499	1.000	.015	.016	-.005	-.017	-.006	.013	.000	.009
	Openheid1	-.039	.010	-.005	.019	.015	1.000	.497	-.001	.000	.014	.002	-.010	-.006
	Openheid2	.031	.009	-.015	.014	.016	.497	1.000	-.015	-.014	.008	.008	-.008	.018
	Voortuin1	-.063	-.005	.002	-.004	-.005	-.001	-.015	1.000	.504	.003	-.007	-.001	-.008
	Voortuin2	-.003	-.013	-.008	-.017	-.017	.000	-.014	.504	1.000	-.008	-.016	-.010	-.018
	Afstand1	-.189	.001	-.004	-.004	-.006	.014	.008	.003	-.008	1.000	.504	.006	.000
	Afstand2	-.063	.014	-.001	-.004	.013	.002	.008	-.007	-.016	.504	1.000	.002	.014
	Activiteit1	.118	-.012	-.009	.007	.000	-.010	-.008	-.001	-.010	.006	.002	1.000	.500
	Activiteit2	.108	-.011	-.006	-.005	.009	-.006	.018	-.008	-.018	.000	.014	.500	1.000
Sig. (1-tailed)	F_Combi	.	.000	.000	.014	.000	.002	.012	.000	.400	.000	.000	.000	.000
	Hoogte1	.000	.	.000	.184	.141	.239	.244	.348	.171	.477	.148	.190	.218
	Hoogte2	.000	.000	.	.303	.410	.348	.137	.451	.289	.379	.475	.248	.333
	Type1	.014	.184	.303	.	.000	.088	.147	.372	.112	.386	.373	.296	.364
	Type2	.000	.141	.410	.000	.	.131	.126	.357	.110	.343	.171	.499	.251
	Openheid1	.002	.239	.348	.088	.131	.	.000	.475	.486	.154	.453	.230	.319
	Openheid2	.012	.244	.137	.147	.126	.000	.	.131	.147	.280	.285	.283	.099
	Voortuin1	.000	.348	.451	.372	.357	.475	.131	.	.000	.400	.306	.460	.278
	Voortuin2	.400	.171	.289	.112	.110	.486	.147	.000	.	.273	.120	.234	.088
	Afstand1	.000	.477	.379	.386	.343	.154	.280	.400	.273	.	.000	.319	.498
	Afstand2	.000	.148	.475	.373	.171	.453	.285	.306	.120	.000	.	.450	.161
	Activiteit1	.000	.190	.248	.296	.499	.230	.283	.460	.234	.319	.450	.	.000
	Activiteit2	.000	.218	.333	.364	.251	.319	.099	.278	.088	.498	.161	.000	.
N	F_Combi	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364
	Hoogte1	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364
	Hoogte2	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364
	Type1	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364
	Type2	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364
	Openheid1	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364
	Openheid2	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364
	Voortuin1	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364
	Voortuin2	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364
	Afstand1	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364
	Afstand2	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364
	Activiteit1	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364
	Activiteit2	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364	5364

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.297[a]	.088	.086	.81402

a. Predictors: (Constant), Activiteit2, Afstand1, Type1, Voortuin1, Hoogte2, Openheid1, Hoogte1, Openheid2, Type2, Activiteit1, Voortuin2, Afstand2

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	341.820	12	28.485	42.988	.000[b]
	Residual	3545.695	5351	.663		
	Total	3887.515	5363			

a. Dependent Variable: F_Combi

b. Predictors: (Constant), Activiteit2, Afstand1, Type1, Voortuin1, Hoogte2, Openheid1, Hoogte1, Openheid2, Type2, Activiteit1, Voortuin2, Afstand2

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	2.253	.011		202.543	.000
	Hoogte1	.153	.016	.147	9.745	.000
	Hoogte2	-.023	.016	-.022	-1.480	.139
	Type1	.014	.016	.013	.864	.388
	Type2	-.087	.016	-.083	-5.532	.000
	Openheid1	-.071	.016	-.068	-4.498	.000
	Openheid2	.067	.016	.064	4.259	.000
	Voortuin1	-.083	.016	-.080	-5.302	.000
	Voortuin2	.041	.016	.039	2.601	.009
	Afstand1	-.220	.016	-.209	-13.836	.000
	Afstand2	.042	.016	.040	2.677	.007
	Activiteit1	.093	.016	.089	5.891	.000
	Activiteit2	.066	.016	.064	4.225	.000

a. Dependent Variable: F_Combi