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A STATED PREFERENCE APPROACH ON THE USE OF E-BIKES IN COMMUTING TRAVEL ANALYSIS

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PREFACE

Writing a thesis is an assignment that you cannot do alone. It involves advice, encouragement and support from different people. Without the help of all those people it would have been very difficult to complete this thesis.

First of all, I would like to thank my supervisor, Professor Dr. Frank Witlox. He helped me finding an interesting topic in the already broad field of transport geography. Through his knowledge of similar research, advice and encouraging words; he helped this thesis become what it is today.

Similar words of thank go out to Filipe Teixeira (Department Geography, Ghent University) for the help and advice in preparing the stated preferences analyses and tips in RStudio. I would also like to thank Dieter Lemaitre for the opportunity to use the LimeSurvey platform and the tips to arrive at a fully-fledged survey. I would also like to thank Steven Lannoo (Institute for Coach and Bus) and Toon Zijlstra (UAntwerpen), who helped me define good research questions at the beginning of this thesis. Thanks also to all the people who shared the survey on social media. A similar word of thank to all respondents who completed the survey. Without them, this thesis would not have yielded any results. Also, a thank you to Ilias for reading this master's thesis on spelling mistakes.

In addition to these people, I would also like to thank my parents for their support during the writing of my thesis and throughout my study career. Specifically, I would also like to thank them for their help in finding and writing to potential respondents. Finally, I would also like to thank Anke for voluntarily listening to my problems and for continuing to encourage me during the writing of this thesis.

Corneel Casier, May 2020

SUMMARY

In this master's thesis, we discuss the potential of e-bikes in commute. Rising sales numbers of e-bikes in Belgium and abroad show that an increasing part of the population can use this transport mode. A large amount of people, in Flanders approximately 60%, lives in e-bike range (+- 15 km) from their work. Policy makers try to stimulate (e-)bikes in commute by investing in bicycle infrastructure and providing financial stimulation (high mileage allowance in Belgium and tax profit when leasing e-bikes). We invest here what is the effect of those and some other factors on the likelihood someone uses an e-bike to ride to work.

We use a stated preference analysis to invest this. Our results suggest that the presence of infrastructure and financial stimulation has a positive effect on the likelihood of e-cycling to work. Yet we see that some other factors have a larger effect. The factors weather, trip time and type of e-bike have a larger effect than infrastructure and financial stimulation. We also see that there is a (minor) role for the employer to facilitate e-cycling to work since the presence of a secured parking with possibility to charge the battery and a shower have a positive effect this mode in commute. Furthermore, we see also some small differences between respondent's characteristics. Females show a larger interest in e-cycling to work than males do. There is as well a difference between e-bike owners and non e-bike owners based on the type of e-bike. When looking at age we see that older respondents show a higher likelihood of e-cycling to work than younger respondents. Our results make it not possible to determine if there exist differences between people living in urban regions and people living in rural regions.

SAMENVATTING

In deze masterthesis bespreken we de mogelijkheden van elektrische fietsen in het woon-werkverkeer. De stijgende verkoopcijfers van elektrische fietsen in België en in het buitenland tonen aan dat een toenemend deel van de bevolking gebruik kan maken van deze vervoerswijze. Een groot deel van de bevolking, in Vlaanderen ongeveer 60%, woont op een afstand van hun werk die met de elektrische fiets kan worden overbrugd (+- 15 km). Beleidsmakers proberen de (elektrische) fiets in het woon-werkverkeer te stimuleren door te investeren in fietsinfrastructuur en het geven van financiële prikkels (hoge kilometervergoeding in België en fiscale winst bij het leasen van elektrische fietsen). We onderzoeken hier wat het effect is van die factoren en enkele andere op de kans dat iemand een elektrische fiets gebruikt om naar het werk te rijden. We gebruiken een stated preference analyse om dit te onderzoeken.

Onze resultaten suggereren dat de aanwezigheid van infrastructuur en financiële stimulering een positief effect heeft op de kans dat iemand met een elektrische fiets naar het werk rijdt. Toch zien we dat enkele andere factoren een groter effect hebben. Factoren zoals de weersomstandigheden, de reistijd en het type elektrische fiets hebben een groter effect dan infrastructuur en financiële stimulering. We zien ook dat er een (kleine) rol is voor de werkgever om elektrisch fietsen naar het werk te faciliteren. Zo zien we dat de aanwezigheid van een beveiligde parkeerplaats met mogelijkheid om de accu op te laden en een douche een positief effect hebben op deze modus in het woon-werkverkeer. We zien ook enkele kleine verschillen tussen de kenmerken van de respondent. Vrouwen tonen een grotere interesse in elektrisch fietsen naar het werk dan mannen. Er is ook een verschil tussen eigenaars van een elektrische fietsen en mensen die geen elektrische fiets hebben, met name op basis van het type elektrische fiets. Als we naar de leeftijd kijken, zien we dat oudere respondenten een grotere kans hebben om met elektrische fietsen naar het werk te gaan dan jongere respondenten. Onze resultaten maken het niet mogelijk om te bepalen of er verschillen bestaan tussen mensen die in stedelijke regio's wonen en mensen die op het platteland wonen.

POPULARIZING CONTENT

The number of e-bikes on the streets has increased significantly in recent years. We can see this increase also in sales figures of e-bikes. At the same time, we see that in Flanders quite a lot of people live relatively close to their workplace. The combination of an increasing number of people owning an e-bike and relatively short distances in commuter traffic means that this sustainable mode of transport has a great potential for these journeys. Thanks to the electric assistance when pedalling, cycling takes less effort. In this way, longer distances can be covered more easily than with a normal bicycle. However, this potential is not yet reflected in figures on the number of electric cyclists commuting between home and work. In this master's thesis, we investigate how various factors influence the choice to ride an e-bike to work.

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LIST OF ABBREVIATIONS

Attributes = the features of a product or service (e. g. price, colour, weather conditions, type of e-bike) in a CBC

CBC = choice-based conjoint

e.g. = exempli gratia (for example)

E-bike = electronic bicycle with or without pedal assistance

i.e. = id est (in other words)

Importance scores = the maximum impact an attribute can have on product choice

Levels = the type or amount of an attribute (e.g., good weather conditions, blue, green, red)

Modal share = the percentage of trips that a certain transport mode, in this case e-bikes, has to all the trips made in an area

Modal shift = the change in transport mode

N/A = not applicable

None-parameter = captures respondent propensity to not purchase any of the choices in a simulation

Part-worth utility = the preference for a level of an attribute

Pedelec = electronic bicycle with pedal assistance

Speedelec/speedpedelec = electronic bicycle with pedal assistance that allows speeds up to 45 km/h in Belgium

Utility = the preference for a certain profile

WTP = Willingness-to-pay

1 INTRODUCTION

The last 15 years a broad range of new transport modes is on the rise. In several cities, e-scooters, cargo bikes, e-steps, e-skateboards, monowheels, car- and bike sharing systems are popping up. One of these upcoming modes of transportation are e-bikes. On the streets, in newspapers, in magazines and advertisements, e-bikes are well visible in our daily lives. Rising sales numbers of e-bike in Belgium and abroad show that a growing part of the population has the possibility to use this transport mode. At the same time, we see that approximately 60% live only 15 km or less from their job in Flanders (IMOB, 2020). This distance may be too far to ride on a regular bike for many people; yet an e-bike can be a plausible alternative for them. The combination of those two factors, a rising popularity of e-bikes (shown in e-bike sales) and the range of an e-bike that is sufficient for home-work trips (i.e. commute) lead to a growing potential for e-bikes in commute. We see as well a call for a more sustainable society. Sustainable transport modes can help achieve this. Policy makers have seen the potential of e-bikes as well and have high expectations of this durable transport mode to improve accessibility and livability in cities and rural villages. In this thesis, we discuss this potential, keeping mind the expectations of the policy makers. Furthermore, we investigate what factors do play a role when e-cycling to work.

In the first part of this master's thesis, a review of the literature is presented with a focus on the role of e-cycling in Belgium, with a focus on Flanders. In addition, we discuss the possibilities of e-bikes in commute. Following this extensive literature review, we formulate a couple of research questions regarding this topic. In the second part of this master's thesis, we investigate these questions by means of a stated preference investigation. The results of this investigation are analysed and discussed. In the final part of this thesis, we formulate a conclusion.

2 LITERATURE REVIEW

To have a better understanding of e-bikes, we present first a literature review. The goal of this is to formulate several research questions that we can examine in the second part of this master's thesis. First, we will discuss a general view of e-bikes. This includes information on what e-bikes are and what subtypes do exist. Further, we will discuss more information on the history of this transport mode and e-bikes in the Belgian and Flemish context. This general view allows us to go further into user characteristics, modal shift and - share of e-bikes. Next, we will discuss what are the distances covered by e-bike users and commuters, followed by an analysis of the advantages and disadvantages of e-bikes. After the disadvantages, we discuss the institutional framework and durability and environmental impact of e-bike. In the last part of the literature review, additional information on commuting in general and (e-)bike commuting in specific is presented.

2.1 General information

Electrical bicycles or e-bikes are a mode of transportation that is very similar to normal biking. At first sight, an e-bike looks similar to a regular bike. However, an addition to e-bikes distinguishes them from normal bikes. This difference is the presence of a battery and some sort of electrical motor on the bike to convert the energy from the battery into support for the cyclist (Cambridge Dictionary (online), 2020b). The main difference between regular bicycles and e-bikes is this 'electrical assistance'. Yet a wide variety of two-wheeled electrical vehicles exists, therefore it is useful to give a clear definition of what is meant precisely by the terms 'e-bike', 'pedelec', 'moped', 'scooter', 'speed pedelec', and other similar terms and what are the differences between those different types.

(A)

(B)

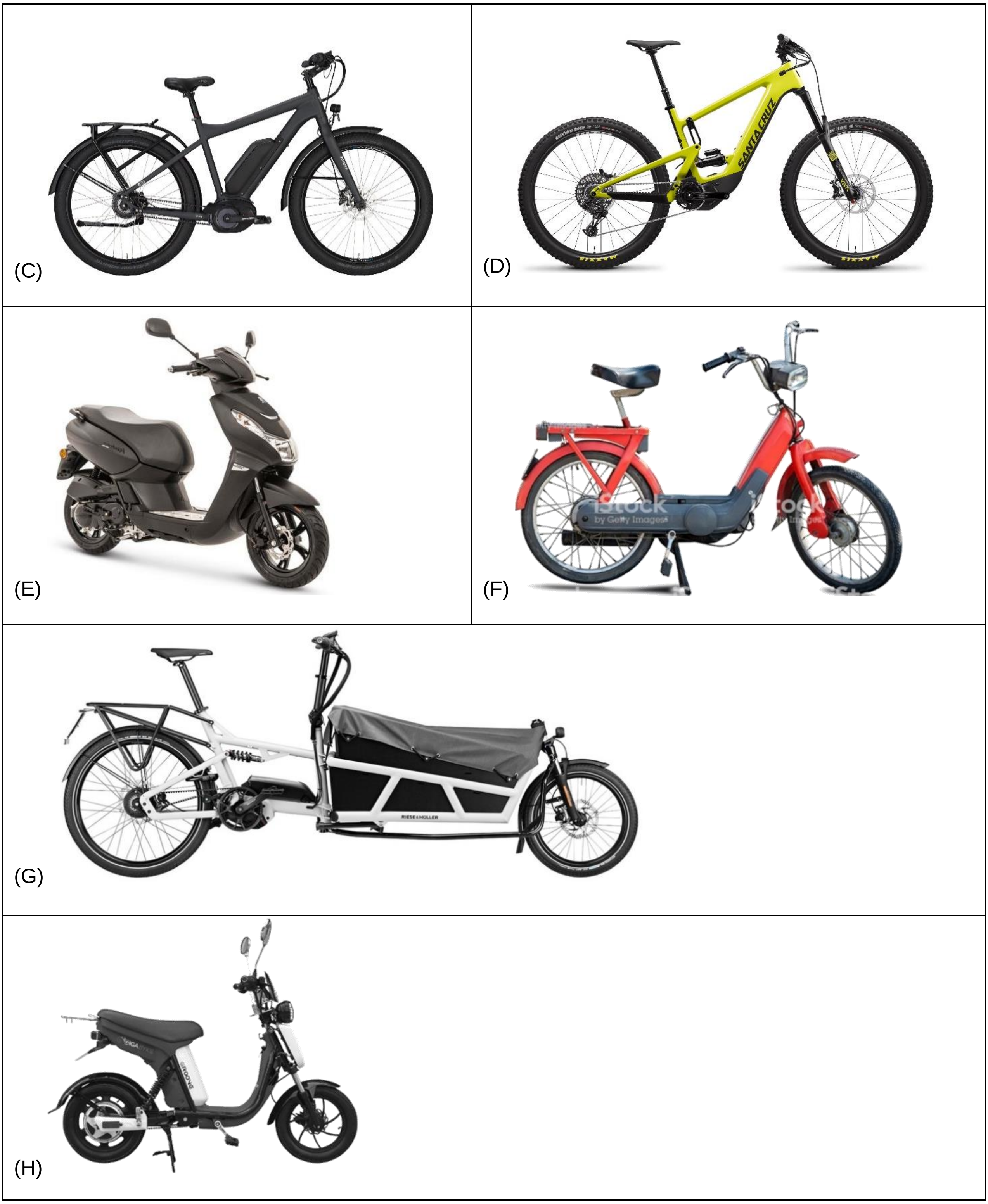


Figure 1: E-bike like vehicles [(A) = a regular bike, (B) = an e-bike (pedelec-type), (C) = an e-bike (speed pedelec-type), (D) = an e-mountain bike, (E) = a scooter, (F) = a moped, (G) = an e-cargo bike and (H) = an

e-bike (non-pedelec type)] (Akakçe, 2020; Deltabikes, 2018; Electric Ride Review, 2020; Fiets.nl, 2020; Fietsonline, 2019; IStockphoto LP, 2019; Riese & Müller, 2020; WKScooterCentre, 2018)

The definition of an e-bike is the following: “a bicycle that has electrical assistance that helps the bicycle move forward. The cyclist can keep on pedalling, but this is no obligation to get support from the electrical motor (i.e. the battery) on the bike” (Cambridge Dictionary (online), 2020b). Picture B on Figure 1 shows an example of an e-bike. On this picture, there is a clear difference with a regular bike, i.e. Figure 1 (A). An e-bike has a battery attached to it. A regular bicycle has evidently no battery or something similar attached to it.

The difference between an e-bike and a scooter is the fact that an e-bike has pedals and a scooter does not. We can set an e-bike in motion by only moving the pedals without the assistance. On a scooter, the propulsion comes solely from the motor. Picture (E) on Figure 1 shows an example of a scooter. A scooter-type vehicle that is very similar to an e-bike is a moped. Figure 1 (F) shows an example of a moped. This transport mode has functional pedals present and the driver can choose whether, the cyclist can use these pedals or not. The main difference between a moped and an e-bike is the type of motor. On an e-bike, this is an electrical motor; contrary, a moped uses a combustion engine that needs petrol oil. There is also a difference in legal requirements for the drivers. To conclude: an e-bike is a bicycle (with functional pedals present) that can give electrical assistance to its driver (Cambridge Dictionary (online), 2020b).

2.2 Subtypes

2.2.1 Pedelecs

Although the definition of an e-bike delineates this transport mode, two main subtypes of this mode do exist. On the one hand, there are ‘pedelecs’. This type of e-bike requires pedalling to activate the motor. If the rider of a pedelec stops pedalling, the motor of the pedelec stops giving electrical support. A sensor on this type of e-bike measures if the pedals move or not. Figure 1, (B) shows a photo of a pedelec type e-bike. The name pedelec, is a contraction of the words pedals (ped-) and electricity (-elec) (Cambridge Dictionary (online), 2020c). Most pedelec-type e-bikes deliver electrical assistance up to 25 km/h. Once you go faster than this speed, the assistance of the motor stops. From this moment on, the assistance comes solely from the driver of the e-bike who is pedalling.

A special subcategory in the pedelec type of e-bike exists. The motor of these pedelecs does not stop giving assistance when riding 25 km/h, but it keeps on giving additional energy and allows the user to reach speeds up to 45 km/h. We call an e-bike of this type a ‘speed pedelec’ or ‘speedelec’. Figure 1, picture (C) shows an example of a speed pedelec. These speedelecs distinguishes themselves from regular pedelecs because the battery is larger. They need this larger battery to give a larger amount of energy. Another characteristic of speedelecs is the license plate they have at the back of their bike (Figure 2, (A)). We will discuss more information on this mode in the section on the institutional framework for e-bikes. Another (smaller) subcategory within the pedelec type is the e-mountain bike (Figure 1, (D)). This is a regular mountain bike (which has a better suspension and bigger wheels than a normal bike) with electrical assistance. People use this type of pedelec more in rural terrains. In cities, we can see another pedelec type frequently, the e-cargo bike. In Flanders, one out of three cargo bikes is electrical. People use this type mostly to transport goods and people (often children) (Figure 1, (G)). Other types of pedelecs are a hybrid style e-bike (a combination of road bike and a mountain bike with electrical assistance) and race type e-bike. The pedelec type e-bike is the most common e-bike in Belgium (Fietsberaad Vlaanderen, 2018; Fishman & Cherry, 2016; Karnap, 2018).

2.2.2 Non-pedelecs

On the other hand, non-pedelec-type e-bikes do exist, Figure 1 (H) shows an example of this type. The electrical motor on these types does not respond to pedalling. A button or a throttle grip on the steer of the bike can switch on the engine. Riders of this type can use the throttle and pedals simultaneously, but different from the pedelec, a non-pedelec e-bike also can get support from the electrical motor when the driver is not pedalling. This category of e-bikes is seen as a sort of moped. Both have pedals and have no requirement to pedal to receive electrical support. This category is rather rare in Western Europe. In Asia, the non-pedelec type of e-bike is very common. When talking about e-bikes in Belgium and by extension all of Europe and North America, we are mostly meaning pedelecs (Karnap, 2018).

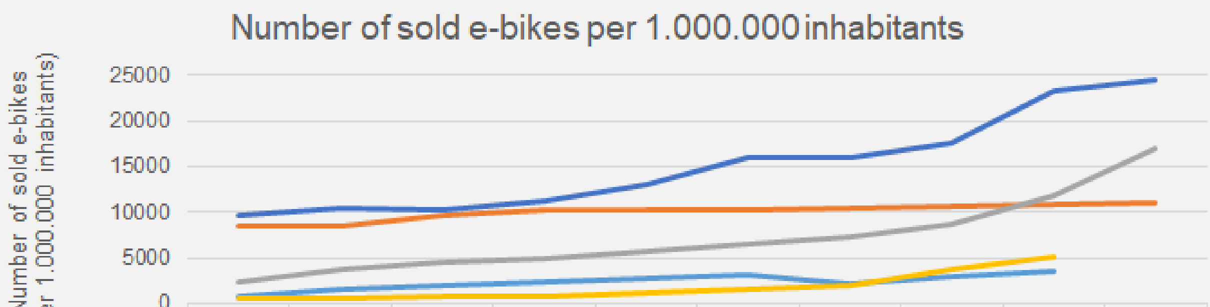
To summarize, e-bikes (pedelec type and non-pedelec type) are in this master' thesis considered as a bicycle like vehicle with functional pedals that can have assistance by an electrical motor. Due to this assistance, riding an e-bike requires less effort (Cambridge Dictionary (online), 2020b, 2020c; Cornwall electric bike tours, 2019; Fishman & Cherry, 2016).

2.3 History

Now we know the definition of an e-bike, we can continue to explore other elements linked to this mode of transportation. The first element that receives further attention here is the history of e-bikes. The invention of the regular bicycle happened around 1817 by Baron Karl von Drais de Sauerbrun. A broad range of innovations followed up this invention. Wellington Adams, Albert Parcelle and Edward Parkhurst already did one of these innovations in the late 19th century, around the year 1885. These men are the inventors of two-wheel electric vehicle technology. They added a motor to a 'regular' bicycle and thus making the first motorized bicycle (Karnap, 2018). This invention needed multiple improvements to make it affordable for the broad public. The battery caused the largest issue here. The first problem was the battery quality. This was for a long time very low in terms of performance and lifetime, while the costs were high. Secondly, the e-bike price was also relatively high due to the high battery cost. These problems lasted until the end from the 20^{th}

century. Yet only from the early 2000's e-bikes became affordable for more people. Especially improvements in technology from the batteries caused prices of e-bikes to drop (Weinert *et al.*, 2007).

This evolution can be seen in number of e-bikes sales. Graph 1 shows the rising sales numbers of e-bikes per one million inhabitants in China, Europe and multiple European countries for the last decade. E-bikes represent one of the fastest growing segments on the transport market. We see a clear rise in the sales numbers in Europe. The Chinese numbers are more continuous. The explosion in the European countries happened in China in the previous decade. In 1998, Chinese factories produced only 40.000 e-bikes, yet in 2005, this number has risen to over ten million. After this exponential growth, the market kept on growing more steadily. The Chinese electric bike market has expanded more rapidly than any other mode during these seven years (Cherry & Cervero, 2007; Fishman & Cherry, 2016; Weinert *et al.*, 2007; Zagorskas & Burinskienė, 2020).

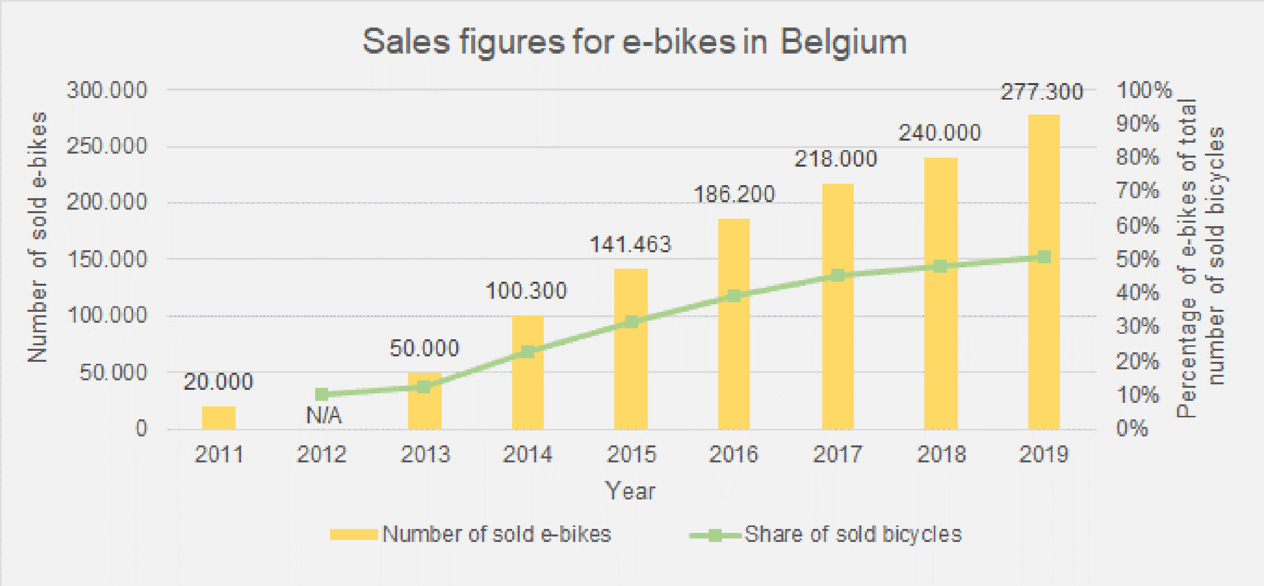


	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Europe	793	1665	2000	2373	2719	3127	2248	2967	3507	
China	8499	8579	9668	10231	10238	10354	10469	10620	10859	11118
Germany	2416	3744	4590	5001	5798	6462	7308	8697	11837	16910
France	567	597	688	845	1157	1523	2000	3807	5046	
Netherlands	9662	10361	10186	11176	12980	16065	15891	17462	23283	24447

Graph 1: E-bike sales worldwide (Apex bikes, 2018; Astegiano *et al.*, 2017; Confederation of the European bicycle industry, 2017; Fishman & Cherry, 2016; Fietsplatform, n.d.; INGS, 2014; Navigant Research, 2018; Statista research department, 2019; Statista research department, 2020)

We need to make an important note on these numbers. As stated before, in China and other Asian countries, there is less a clear definition of what is counted as an e-bike. Often motorized two-wheelers (i.e. scooter style electric bicycles) are also included in the numbers and literature on e-bikes. In Western countries, the definition of an e-bike is as described in this paper.

In Belgium, e-bikes sales are also clearly on the rise the last couple of years. Graph 2 shows the sales numbers of the last decade in Belgium. We see that the number of e-bikes is continuously rising. The total number of sold bicycles (e-bike and non e-bike) is more or less constant, this makes that the share of e-bikes in this number also keeps on growing. We see that last year (2019) half of all sold bicycles in Belgium was an e-bike. These numbers show the great impact e-bikes have in the bike industry.

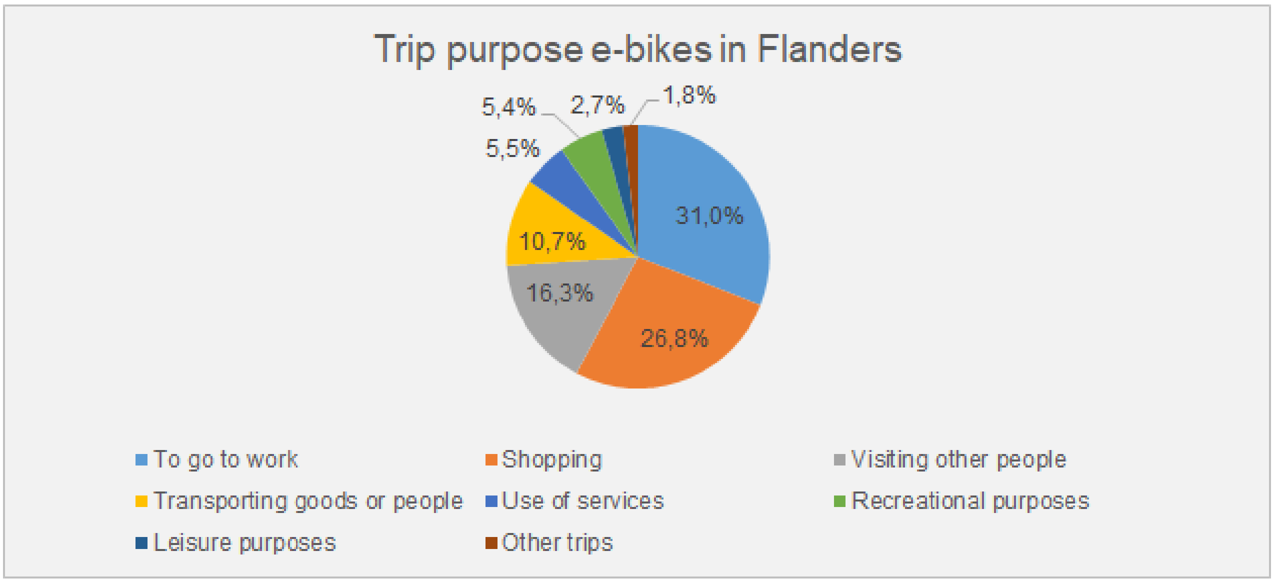


Graph 2: E-bike sales in Belgium (Becycled, 2017; De Morgen, 2018; De Standaard, 2015; Fietsberaad Vlaanderen, 2018, 2019; GVA, 2020; Knack, 2019; O2O, 2020; Sport.be, 2014; VRTNWS, 2018)

2.4 E-bikes in Belgium and Flanders

E-bikes sales are clearly on the rise in Belgium. This causes more and more people to own an e-bike. The most recent figures from the Belgian Federal Public Service for Mobility show that 17,8% of the Flemish households owns at least one e-bike. The same number for regular bikes is 75% (IMOB, 2017, 2020). The annual study of Vias shows similar numbers for e-bike-ownership in Flanders and Belgium. In 2018, 10% used an e-bike, in 2019, 13% and 16% in 2020. 22% of the asked respondents in Flanders has used an e-bike. In Brussels this is 8% and in Wallonia, only 6%. This made 16% for the total of Belgium (Vias, 2020).

The trip purpose for Flemish e-bike users is presented on Graph 3. E-bikes are mostly used to go to work (31%) or to go shopping (26,8%). E-bikes are also used to visit other people (16,3%) and to transport goods or people (10,7%). Beside those trip purposes, e-bikes are also used to make use of services (5,5%) (e.g. going to a doctor), recreational purposes (5,4%), leisure purposes (2,7%) and other trips (1,8%) (IMOB, 2020; Van Cauwenberg *et al.*, 2019).



Graph 3: Trip purpose e-cyclists in Flanders (IMOB, 2020)

2.5 User characteristics

2.5.1 Age

To have a better understanding of e-bikes, a view on the characteristics of e-bike users is useful. Although multiple studies did research on the user characteristics in different regions, they found similar results. When looking at the age of e-bike users, we see a certain shift has happened. The studies of Cherry and Cervero (2007), MacArthur *et al.* (2014) and Wolf and Seebauer (2014) found that the average age of e-bike users is higher than of regular cyclists. An *et al.* (2013) and Fyhri and Fearnley (2015) did not found significant differences in age of e-bike users.

In Belgium, the age of e-bike users has undergone a certain evolution. In 2015, e-bikes were mostly (96%) in the older age categories (older than 46 years). Three years later, this has evaluated into a larger spread of users. 9% in the category between 18 and 25, 10% of the e-bikers are between 26 and 35 and 13% between 36 and 45%. The share of e-bike users older than 46 represent in 2018 only 68%. In this evolution, we clearly can see the shift in the thinking that e-bikes are only for elderly people to the way e-bikes are now broadly accepted by all age categories (Becycled, 2017; De Standaard, 2014; Fietsberaad Vlaanderen, 2015; Fietsberaad Vlaanderen, 2018; Fishman & Cherry, 2016; Vias, 2020).

2.5.2 Gender

When we look at the gender, the academic literature mostly suggests that most e-cyclists are male. MacArthur *et al.* (2014) and Johnson and Rose (2013) found that respectively 85% and 71% was male. Fyhri and Fearnley (2015) show that although e-bike users are mostly male, e-bikes have a greater effect on female than on male cyclists. An *et al.* (2013) did not found significant differences in gender of e-bike users. Here it is important to note that the location of the study of An *et al.* (2013) was in China and the other studies were located in the Western world. A similar study in Flanders, shows other results, 41,3% of e-bike users are male and 58,7% are female (Gemeente- en stadsmonitor Vlaanderen, 2017; IMOB, 2017).

2.5.3 Educational background

The educational background of e-cyclists is similar over different studies examining this topic. We observe that e-bike users often do have higher educational attainment than regular cyclists do. MacArthur *et al.* (2014) state that 34% of e-bikers have a graduate degree. Cherry and Cervero (2007) and Johnson and Rose (2013) found that e-bike users respectively in China and Australia have significantly a higher educational background than regular cyclists.

2.5.4 Income

Closely related to the educational background of e-bikers, is their income. Cherry and Cervero (2007) and Johnson and Rose (2013) found that the income of e-bike users in China and Australia is significantly higher than that of regular cyclists.

2.6 Modal shift & modal share

An element that relates closely to studies of the characteristics of e-bike users is the *modal shift* to e-bikes. Modal shift means the change in transport mode, in this case focused on the change from any other transport mode than e-cycling towards e-bikes. It answers the question what mode someone used if an e-bike was not available. Knowing what mode the e-bike mostly replaces is useful in policy actions and assessing the environmental impact of e-bikes (Sun *et al.*, 2020; Wolf & Seebauer, 2014). Research in different contexts tries to reveal this modal shift. The results of this research show slightly different results, mostly depending on the local context, yet it shows some general trends. E-bikes mostly replace conventional cycling and to a lesser extent public transport (An *et al.*, 2013; Astegiano *et al.*, 2017; Cherry & Cervero, 2007; Jones *et al.*, 2016; Sun *et al.*, 2020). E-bikes seldom generate a modal shift from cars to e-bikes (An *et al.*, 2013; Berjisian & Bigazzi, 2019; Kroesen *et al.*, 2017). Only for short distance car journeys, e-bikes offer sometimes an alternative. As stated before the local context influences this modal shift heavily. In car-dominated countries, e-bike mainly replace car trips. In countries and cities that have high quality transit systems available, the shift is primarily from those public transit modes towards e-bikes (Fishman & Cherry, 2016; Edge *et al.*, 2018; Kroesen, 2017; Van Cauwenberg *et al.*, 2019).

Alongside the modal shift, the modal share is important to assess the current and future potential of e-bikes. The modal share is the number of trips that a certain transport mode, in this case e-bikes, has to all the trips made in an area. The modal share of e-bike has clearly risen throughout the years in Flanders, from 0,9% in

2016, to 1,1% in 2017, to 1,4% in 2018, to even 2,4% in 2019. To compare, the modal share of regular bikes 14,4%, 64,7% for cars and 12,3% for pedestrians (IMOB, 2020).

Astegiano *et al.* (2019) show some future scenarios for the modal share of e-bikes. Depending on the country and policy scenario, they see a growth in the share of e-bikes from 1% in 2015 to between 2,2% and 4,5% in 2050. The scenario with a growth to 4.5% is valid in the leading countries (i.e. the countries with already a large modal share of regular cyclists). In this scenario, from 2020 onwards, policy needs to start penalising cars and rewarding cycling. The scenario with less growth (only to 2,2%) is applicable in non-leading countries and where policy is not adjusted in favour of cycling.

2.7 Pros and cons

2.7.1 Advantages

The most important element to choose to ride an e-bike are the advantages of an e-bike over other transport modes. Knowing the benefits from e-bikes is important to understand this choice. The first one is the offer of an alternative for people who for various reasons are averse to cycling. Regular cycling has multiple disadvantages. These are bad infrastructure, severe weather conditions (wind and rain), hard to cover large distances, riding uphill, unsafe feeling in traffic, fear of theft, bad air quality, sweating due to physical effort, hard to carry luggage or transport other persons and lack of good parking. Thanks to the electrical assistance, e-bikes solve some of the stated disadvantages of regular bikes. The electrical assistance gives the sensation of cycling with a tail wind or slightly downhill. This makes it easier to ride longer trips and to cover hilly terrains.

The solved disadvantages of regular bicycles are therefore the larger distances, hills and physically strenuous. At the same time, an e-bike offers many of the same benefits as the motorized transport like a moped or a car (larger range, high flexibility and higher rush-hour speed in an urban context) (De Tijd, 2018; Dill & Rose, 2012; Fishman & Cherry, 2016; Fyhri & Fearnley, 2015; Plazier *et al.*, 2017; Popovich *et al.,* 2014: Rotthier *et al.*, 2017).

The main advantage of e-bikes is an increase in speed without additional effort. Multiple studies in Belgium (Astegiano *et al.*, 2017; Lopez *et al.,* 2017; Vias, 2020) and abroad (Berjisian & Bigazzi, 2019; Zagorskas & Burinskienė, 2020) show that the average speed of e-bikes is significantly higher than the speed of regular bikes. The average trip speed for e-bike approximately 20 km/h. This speed is substantially higher than the average speed of a regular bicycle, between 12 and 15 km/h. Furthermore, the speed of a speedpedelec is obvious higher than the speed of a regular e-bike. Studies show that the average speed of a speedpedelec is between 30 and 36 km/h (Cherry & MacArthur, 2019; Rotthier & Cappelle, 2017; Steintjes, 2016).

This increase in speed makes it possible that an e-bike offers competitive travel speeds compared to local public transport and rush hour driving in urban context. Another advantage is the energy efficiency of an e-bike. Academic studies show that the energy efficiency is better than that of any other mode of transport (except a traditional bike), even walking! The e-bike is therefore environmentally superior to other motorized modes of transport (Dave, 2010; Rotthier & Cappelle, 2017; Wiederkehr, 2012). They even state about e-bikes: "(E-bikes) have the potential to replace many car and public transport trips, all to the benefit of the environment, public health and other motorists." (Fyhri & Fearnley, 2015, p. 46).

The main reasons of e-cyclists to choose this mode as their main travel mode are punctuality, timesaving, economic, labour saving and convenience. For many, riding a regular bike to work is too laborious due to the long travel distances. If they take the bus, it is too crowded and expensive. Furthermore, due to the congested roads during peak time, busses take too long to reach their destination and punctuality cannot always be guaranteed. Taking all these factors in mind, gradually more people choose the timesaving, economic, labour-saving and convenient e-bikes as their main travel mode (An *et al.,* 2013*)*. Similar results in other studies found that the main advantages of e-bikes are greater speed and acceleration than regular bikes with less exertion. They also enable more people to bicycle, more trips and are more fun for users (Popovich *et al.,* 2014; Van Cauwenberg *et al.*, 2019). The stated advantages of speedelecs are very similar. Users state that speedelecs are punctual, economically advantageous, ecologically advantageous, active, silent and fun (Rotthier *et al.*, 2016).

Another advantage of e-bikes is the used space they occupy. Compared to several other modes, we see that the used space of an e-bike is one of the lowest. A regular bicycle uses between 1,2 and 1,6 m², an e-bike is similar between 1,2 and 1,7 m², a moped between 1,2 and 2.0 m², public transport between 0,5 and 1,0 m², a car between 5,0 and 12,0 m² (Zagorskas & Burinskienė, 2020). Especially for parking space this important. Rotthier *et al.* (2017) argues that on one car parking can stall up to ten e-bikes.

The last element that is an advantage of e-bikes is the impact on the health of users. Results show that e-cyclists do have more physical exercise because they ride longer distances and do more trips (An *et al.*, 2013; Fyhri & Fearnley, 2015). These more regular and longer trips with the assistance of a battery compensates for less effort per kilometer than a regular bike (Berjisian & Bigazzi, 2019; Bourne *et al.*, 2018; Hansen *et al.*, 2018). Health is therefore an important factor in the choice to e-bike, especially for older people (Jones *et al.*, 2016). Important to note here is that most studies found that e-cyclists need sufficient safe bike infrastructure, otherwise, insecurity in traffic negates these health benefits (Hansen *et al.*, 2018).

2.7.2 Disadvantages

Although e-bike use has multiple benefits as discussed in the previous paragraphs. There are as well, as any transport mode, some disadvantages related to them. Similar to normal bikes, an e-bike offers no solution when we need to transport bigger loads. This is not a problem while commuting, because bike pockets offer for most people a solution to carry some smaller items. Another problem for e-bikes is the weather. Riding an e-bike offers like a regular bike, no protection against precipitation, like rain, hail or snow. A third issue is the fact when riding an e-bike outside urban areas, motorized transport is faster than regular e-bikes (Heinen *et al.*, 2010). The cited negative aspects of e-bikes according to users are a lack of security and safety concerns, unwieldiness and range anxiety (Edge *et al.*, 2018; Fyhri *et al.*, 2017; Popovich *et al.,* 2014). Rotthier & Cappelle (2017) similarly found that this feeling of unsafety in traffic. This feeling is mainly linked with insufficient adjusted cycling infrastructure. They note that complex traffic nodes, wells and bumps in the road and no free cycling infrastructure due to parked cars makes e-cycling unsafe.

The weight of e-bike is another element that many see as a disadvantage. This is mainly due to the battery and the motor of an e-bike that add a 50% addition of weight. Not only these two elements make it heavier, also manufacturers make an e-bike stronger (and therefore heavier) to be able to carry those extra weights (Fietsberaad Vlaanderen, 2013; Jones *et al.*, 2016; Van Cauwenberg *et al.*, 2019). A last element that users often see as a disadvantage of e-bike is finding safe, adjusted parking. This is not always possible for the heavier e-bikes, especially linked with theft concerns (Edge *et al.*, 2018; Fietsberaad Vlaanderen, 2013; Rotthier & Cappelle, 2017).

2.8 Safety

One of the main subjects about e-bikes that gets attention in the mainstream media is safety. In the academic literature, there are two main views of regarding this topic. One group sees e-bikes as more 'dangerous' than regular bikes. According to them, contributing factors to crashes are the heaviness of an e-bike (the added battery and motor affect the equilibrium of an e-bike, making it more unstable), increased speeds and cycling without protection. Due to higher speeds, crashes and collisions can happen more easily. There are two reasons for this. On the one hand, e-bikers (especially first-time e-bikers and elderly people) are not used to the speed they can generate on their bike. Normally, when riding a regular bike, they ride at a more moderate speed and have more time to adjust their route. On a higher speed, the time to react decreases. On the other hand, other road-users need to adapt to this recent form of transportation as well. They see someone riding a bike, without realizing that this is an e-bike. This type of bike will be there faster and so there is less time to make a manoeuvre. Evidence so far shows that e-bike users are subject to slightly higher risks of injury, with the knowledge that databases often make no distinction between the different type of bicycles (Berjisian & Bigazzi, 2019; Cherry & MacArthur, 2019; Fietsberaad Vlaanderen, 2015; Fishman & Cherry, 2016; Popovich *et al.,* 2014; Zagorskas & Burinskienė, 2020).

Other literature suggests that the perceived safety is in some situations higher than of regular cyclists. E-cyclists feel so because they can traverse (dangerous) intersections faster than with a regular bike. This causes that clearing a dangerous point goes faster (Berjisian & Bigazzi, 2019; MacArthur *et al.*, 2014; Weinert *et al.,* 2007).

A possible solution to have less severe head injuries is an obligation from the government to require people to wear a bicycle helmet. Especially when riding an e-bike. In Australia, Argentina and New Zealand bicycle helmets are compulsory for everybody who rides any type of bike. In some other countries, there is some specific legislation on helmets while riding an e-bike such as in Portugal, Russia and Singapore (Bicycle Helmet Safety Institute, 2019). In Flanders, 15% of the cyclists wears on all occasions a helmet (Fietsberaad Vlaanderen, 2018). There is no specific legislation on helmets in Belgium or Flanders, only speedelec-drivers need to wear a helmet.

2.9 Institutional framework

There is besides a possible cycling helmet law, an important role for the national government to regulate e-cycling. The Belgian government makes a distinction between the two categories of e-bikes, speedelecs and other e-bikes. As discussed before, these regular e-bikes give assistance up to 25 km/h. The Belgian legislation considers a normal e-bike as a regular bike. A rider has the same rights and duties as a normal bike. A e-cyclist must follow the traffic signs of regular bikes and if present ride on cycling lanes.

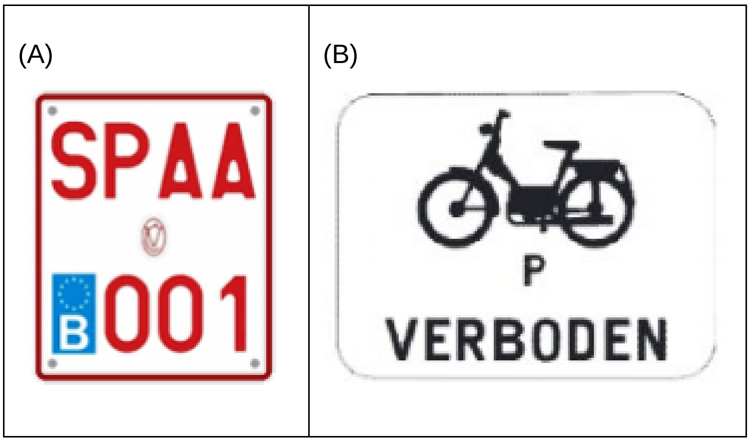


Figure 2: Speedelec attributes (Rotthier & Cappelle, 2017)

A second category with more adjusted rules, is the one of the speedelecs. European and Belgian legislation considers speed pedelecs as a special category of mopeds, called: ‘category P’. In Belgium there are some obligations related to having a speedelec. You need to have a license plate for the e-bike, Figure 2 (A). This consists of the letters ‘SP’ for *s*peed *p*edelec in combination with a unique combination of letters and numbers. It is also compulsory to wear a helmet when driving a speedelec and it is mandatory to have a driving license for any other vehicle (apart from a driving license type G, for riding agricultural vehicles). This causes that only a person that is at least older than sixteen years in Belgium (the youngest age it is possible to obtain the license to drive a moped (category AM)) to ride a speed pedelec. It is also obliged, contrary to a regular bike, to have an insurance when driving a speed pedelec (Rotthier & Cappelle, 2017).

There are as also some specific rules where a speed pedelec can drive on the road. When the speed limit for cars is 50 km/h or lower, speed pedelecs drivers can choose if they ride on the bike lane or on the road, while respecting the maximum speed. When the speed limit is higher than 50 km/h, speed pedelec are obliged to ride on the bike lane. The road authority can, if needed, place a special road sign. Figure 2 (B) shows an example of such sign. This indicates whether a speedelec can cycle in a certain street (Fietsersbond, 2015; Rotthier & Cappelle, 2017).

In addition to the rules in the Road Code, tries the Belgian government to do multiple actions to promote sustainable modes of transport, such as the electric bicycle. The first one is stimulating companies to lease e-bikes to their employees. The costs incurred to encourage sustainable mode of commute, i.e. a speedelec or other type of e-bike, were 120% deductible as professional expenses for the self-employed and company managers until the end of December 2019. From 2020 onwards, the policy has reduced this rate to 100%. In 2014, 75% of the leased bicycles (in total between 40.000 and 50.000) are e-bikes (De Standaard, 2014).

Another element to encourage cycling is the mileage allowance that the employer pays to its employee to ride a bicycle to work. In Belgium this allowance is set at 0,24 € per kilometer travelled. The mileage allowance is tax exempt and employees do not need to pay social security contributions from it. E-bikes are no exception to this (De Tijd, 2018; FOD Financiën, 2020; Fedweb, 2019). Belgium has the largest tax benefit of the European Union for commute by bicycle. The benefit in Belgium is twice as high as in the Netherlands, the country that after Belgium gives the largest tax benefit to cyclists (De Standaard, 2019).

Beside the benefits in taxes, also the infrastructure plays an important role. Mueller *et al.* (2018) show that there is a link between the number of cycling lane km per 100.000 inhabitants and the number of (e-)cyclists. Therefore, having more cycling infrastructure will not only increase the number of regular cyclists but also e-cyclists. The Flemish government has stated in their coalition agreement the following about the investment policy in the mobility sector: "The focus of the investment policy is on the commuter traffic and commuter school traffic. We are striving to an ambitious modal shift. The share of sustainable modes on foot, by (e-)scooter, (e-)bicycle or speed pedelec, owned or via sharing systems, and by collective transport or taxi should increase to at least 40% for the whole of Flanders." (Vlaamse Regering, 2019, p. 178). This shows that the Flemish government tries to improve the modal share of e-bikes, among others, by investing in cycling infrastructure.

2.10 Distance

2.10.1 Distances covered by e-bikes

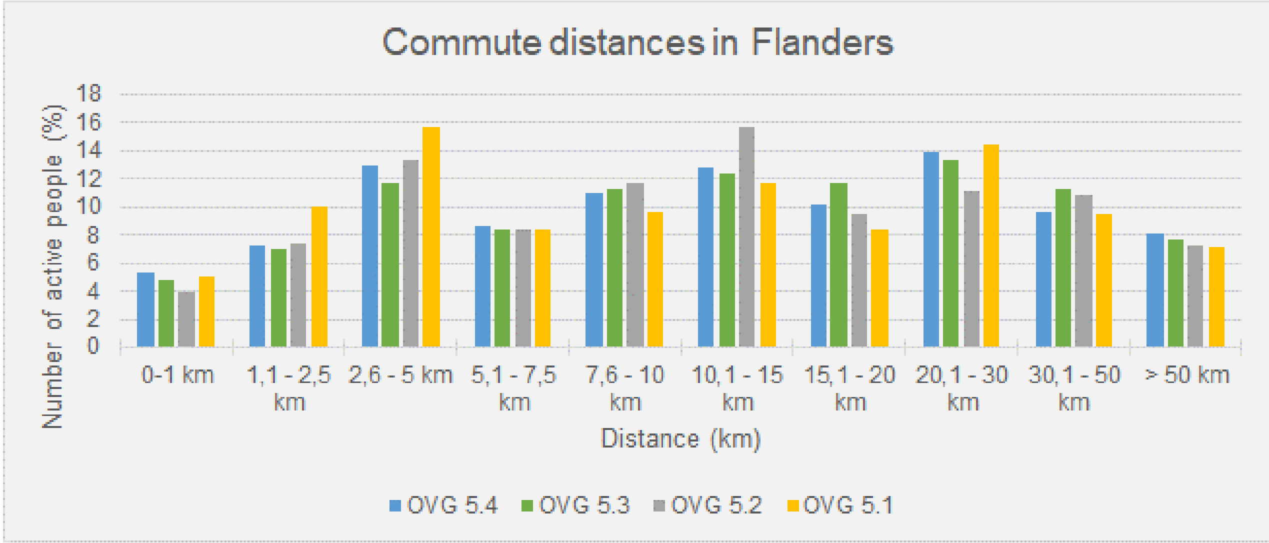
Closely related to the main advantage of e-bikes, an increase in the average trip speed, is the average trip distance of an e-bike. Having an understanding of this, is important to know what the potential of e-bikes in commute is. Academic studies on this topic show similar results. Trip distances with an e-bike increase compared to a regular bicycle. Exact numbers differ depending on the type of investigation and context. Zagorskas and Burinskienė (2020) state that the typical trip distance for an e-bike is between 500 m and fifteen km. Their study found for competing modes the following: between 500 m and eight km for a regular bicycle, between one and twenty km for a moped, between one and twenty km for public transport and between two and 35 km for a car. Fyhri and Fearnley (2015) found an increase in average (e-)cycling-trip distance from 4,8 km (with regular bicycle) to 10,3 km (with e-bike). Berjisian and Bigazzi (2019) found an average single trip distance of 6 km and a weekly total distance of 60 km. Astegiano *et al.* (2017) and Lopez *et al.* (2017) found an average trip distance of 6,6 km in the city of Ghent. Similar results are visible in data for Flanders. When someone uses an e-bike, they use it mostly for distances smaller than 5 km (59,3%). For distances longer than 5 km, an e-bike is less used (40,6%). For larger distances than 15 km e-bikes are seldom used, hence only 7,3% of all e-bike trips covers distances longer than 15 km (Gemeente- en stadsmonitor Vlaanderen, 2017; IMOB, 2020). Other numbers of Flanders show that the distance of an average e-cycling trip is 9.4 km and for a normal cycling trip, this is 4.8 km (Fietsberaad Vlaanderen, 2013). The secretary-General of Flemish mobility department stated similar distances. Regular bicycles have a range of around 10 km. The range of e-bikes is larger and is between 20 and 30 km (Filip Boelaert, November 2019, personal communication). Rotthier *et al.* (2017) stated similar findings.

Sun *et al.* (2020) found different e-bike distances depending on the trip purpose. For a commute trip is 8,5 km, this is longer than the distance of other trip purposes like shopping (3,1 km), leisure (4,6 km), transporting people or goods (2,3 km). An *et al.* (2013) found that the average commuter length of e-bike users is 9.54 km.

2.10.2 Commute distances

These findings support the fact that e-bikes may be an interesting transport mode in commute. We define commute as 'the regular journey between work and home' (Cambridge Dictionary (online), 2020a). When we look at the distances for commuters in Flanders between 2016 and 2019 (Graph 4), we see that approximately more than 60% of the working population lives closer than 15 km from their work and around 68% lives closer than 20 km from their work[1] (IMOB, 2017, 2018, 2019, 2020).

1	*% of the population that live closer than 15 km*	*than 20 km*
OVG 5.1 (discusses 2015)	60,5%	68,8%
OVG 5.2 (discusses 2016)	60,5%	69,9%
OVG 5.3 (discusses 2017)	55,5%	67,1%
OVG 5.4 (discusses 2018)	57,9%	68,0%



Graph 4: Commute distances in Flanders (IMOB, 2016, 2017, 2018, 2020)

An *et al.* (2013) found similar results in China, they state about the commuting length of e-bikers the following: "The proportions of users with commuting length longer than 10 km, between 5 km and 10 km and shorter than 5 km are respectively 30%, 37% and 33%. This result indicates that e-bike has strong adaptability in a large travel length range, and e-bikes have become a strong competitor to bus in the middle- and short-length commuter trip service." *(*An *et al.*, 2013, p. 1833).

2.11 Durability and environmental impact of e-bikes

Beside all the technical and institutional related topics, e-bikes have also an influence on the environment. Some aspects of e-bike usage are environmentally positive, while others are negative. As discussed before, the energy efficiency of e-bikes is very high. E-bikes have a lower environmental impact than motorized transport. As we have seen, the modal shift to e-bikes is mostly from already durable modes of transport, like public transport and bikes. The shift is seldom from private motorized vehicles like cars and motorcycles (An *et al.,* 2013). Negative elements of e-bikes on the environment are the generation of electricity and battery disposal (Cherry *et al.*, 2009; Edge *et al.*, 2018).

Multiple studies investigate the emission impact of e-bikes. Their results show that on average each e-bike adoption is expected to result in approximately 460 kg CO_2 net emissions reduction per year (Berjisian & Bigazzi, 2019; Engelmoer, 2012; Popovich *et al.*, 2014; Weinert *et al.*, 2007). This number evidently depends how much car trips an e-bike displaces, i.e. the modal shift (Astegiano *et al.*, 2019; Berjisian & Bigazzi, 2019; Engelmoer, 2012; Sun *et al.*, 2020). Rotthier and Cappelle (2017) argue that an e-bike emit twenty time less carbon dioxide than a car.

2.12 Commute

As we discussed before, one of the main trip purposes of e-bike is commute (31,0% in Flanders) and a rising number of people owns an e-bike. We have seen as well that many people live in comfortable e-bike range of their work or school, distance is less than 20 km for 68% of the Flemish population (IMOB, 2020). This causes that e-bikes may be an interesting alternative in commute. In this paragraph, we focus by which transport mode people do this. To determine if an e-bike has potential in commute-related travel, we need more information about the determinants of commute. In what follows, we will discuss this subject further. What are the needs and expectations of commuters?

When determining the potential of e-bikes in commute, we must look at it as a functional transport mode and not a recreational one. Since the literature of e-bike commuting is limited, we will look first have a background of regular bikes in commute. We will see that e-bikes offer a solution to some of the limits of regular bikes in commute.

2.12.1 Bicycle commuting

Rotthier *et al.* (2017) found that there are several disadvantages of bicycle commuting. These are the following: infrastructure, weather conditions (wind and rain), shortage of bicycle parking, hard to travel longer distances, slopes are exhausting, feeling unsafe in traffic, fear of theft/vandalism, poor air quality, sweating and too difficult to transport luggage (or persons). Heinen *et al.* (2010) state similarly that there are multiple factors influencing bicycle commuting. In their article they state: “Cycling also has a number of disadvantages, including a greater physical effort, the difficulty of carrying loads while cycling, being at the mercy of the weather, and, outside urban areas, travelling more slowly than motorized transport. Factors such as physical effort and speed also limit the distance that a cyclist can travel.” (Heinen *et al.*, 2010, p. 59). Furthermore, the study from Heinen *et al.* (2010) shows that an increase in distance results in a lower mode share for cycling. Other factors influencing bicycle commuting are bicycle infrastructure, facilities at work (shower and bike parking), natural environment (hills, climate, seasons and weather), income, gender, habits, travel time, costs and mileage allowance (Heinen & Buehler, 2019; Vanoutrive *et al.*, 2009; Wardman *et al.*, 2007).

Sears *et al.* (2013) focus on the effect of weather (temperature, wind, snow depth, precipitation and number of hours of daylight) on the likelihood someone commutes by bicycle. In their study, they find that weather clearly effects the likelihood of non-motorized transport. The harsher the weather, the lower the likelihood someone goes by (e-) bike. Although an e-bike offers no protection against precipitation, it makes riding in windy conditions more comfortable.

Academic literature focussing on infrastructure states that bike paths and bike lanes also have an important influence in bicycle commute (Buehler & Pucher, 2012; Howard & Burns, 2001; Mueller *et al.*, 2018; Vanoutrive *et al.*, 2009). Cyclists adjust their route to profit from better roads and cities with safer cycling options have lower car ownership and have a higher gradient of people cycling to work. By comparison, the annual precipitation, the number of cold and hot days, and public transport supply were not statistically significant predictors of bicycle commuting in large cities.

Cycling to work beholds also some dangers. Aertsens *et al.* (2010) show that bicycle commuting in Belgium has a rather high number of accidents. They discovered that there are approximately 10,2 accidents per 10.000 trips. From this number, 23% of those accidents had only material damage, 47% of those accidents led to limited injuries like a bruise or cramp, 30% led to injuries that are more serious.

2.12.2 E-bike commuting

As we have seen before, an e-bike offer a solution to some of these problems. It reduces the physical effort (yet this is not entirely absent) and the travel speed is higher than a regular bike. This makes that problems such as sweating, greater physical effort, slopes and a limited speed also limit the distance that a cyclist can travel are reduced (Rotthier *et al.*, 2017).

When we compare the percentage of kilometers that is done on an e-bike to go to work with a regular bike, we see that 42,9% of the e-bike kilometers are in commute and only 16,5% for a regular bike (IMOB, 2020). In addition, Lopez *et al.* (2017) found that e-cyclists perform the majority of their trips during the typical hours when riding to or from work. This suggests a tendency of people to use an e-bike as a commuting mode.

When we look at the number of people e-cycling to work, this is nowadays rather low. Yet e-bike commuting is rising more and more. An *et al.* (2013) and Sun *et al.* (2020) show that the trip purpose of e-bike users is respectively 42,7% and 39,3% to commute. When looking at Belgium, the trip purpose of e-biker users is 31,0% to commute (i.e. Graph 3) (IMOB, 2020). We see furthermore, that e-bike trips represent throughout the years 1,0% in 2015, 1,6% in 2016, 2,3% in 2017 and 4,6% in 2018 of all commute trips (IMOB, 2017, 2018, 2019, 2020). For comparison, bicycles represent 11,7% of all commute trips, cars 68,5%, public transport 9,8% and on foot 3,4% in 2018. These numbers show that there is clear potential for e-bikes in commute in Flanders, especially when compared with the approximately 60% of people living closer than 15 km from work.

2.13 Problem definition

An interesting statement that shows the possibilities for cycling in in commute in Belgium is the following: “The percentage of people who live within 5 km of their work who commute by bicycle is relatively low (19%), and the majority (more than 53%) use their car. There is hence great potential for a shift from car to bicycle for short commutes. However, there are several societal, economic and environmental factors that dissuade people from cycling. These include a lack of cycling infrastructure, the topography, weather, road accidents, and company-related constraints. They need to be clearly identified to help policy makers to mitigate them and to promote bicycle use in Belgium. Such findings could then support the implementation of adequate policies in favor of a modal shift from car to bicycle commuting, at least for short distances." (Vandenbulcke *et al.*, 2011, p. 119).

Although this statement focusses on regular bicycles, the argumentation they use in this statement also works and is maybe even more applicable for e-bikes. As we have seen throughout the literature review, e-bikes may be an interesting and promising alternative mode in commute. Some of the characteristics of e-bikes solve the disadvantages of regular bicycles. E-bikes have higher average speeds than regular bicycles, this allows to cover larger distances in the same amount of time. Furthermore, it is more environment friendly than cars (and is even faster than cars in an urban context) and mopeds. Similarly, it gives more freedom than public transport. We have seen that e-bikes can cover larger distances (a range between 15 and 30 km) than normal bicycles and commute distances in Flanders are for most people in this range (60% and 68% lives only respectively less than 15 and 20 km from work) (IMOB, 2020). This knowledge allows us to consider that e-bikes could offer an interesting alternative for cars or public transport to commute over these larger distances. At the same time, we see that in Flanders, more and more people start to own an e-bike (17,8% of the Flemish households owns) and this number is on the rise. Yet only a very limited number of people (14,0%) choose to transport themselves by bike in commute and only 3,9% by e-bike to work and 0,3% to school (IMOB, 2020) These low numbers show, similarly to the numbers in the quote of Vandenbulcke *et al.* (2011), only a glimpse of the untapped potential of e-bike in commute.

As we have seen, multiple elements do play a role in (e-)bicycle commute. Some aspects are individual; other factors are physical or environmental and there exist as well policy-related factors (Vanoutrive *et al.*, 2009). Numerous researches are done regarding these factors related to regular bicycles. Yet, there exists only limited research on this topic regarding e-bikes.

In this thesis, we will investigate how contextual elements affect e-bike commute. Are these effects similar to those of regular bicycles or are there differences? And what effects have the largest impact? A better understanding of the preference of (potential) e-bike users of those elements can be useful for policy makers to mitigate a shift towards e-bikes. The aspects that users prefer should be further stimulated in policy decisions. At the same time, our results will also show what the unwanted or unnecessary characteristics are. The contextual element we will investigate here, related to e-bikes in commute, are the presence of a secured parking, the type of e-bike, the trip time, the type of weather conditions, the presence (cycling) infrastructure, the presence of a shower and the presence of additional financial intervention by the employer. How does each of those factors influence the preference structure for e-bikes in commute? And what factors have the largest influence? To answer these questions in a Flemish context, we focus here on Flemish commuters, e-bikers and non-e-bikers.

Our hypotheses for the different questions are the following: weather and infrastructure have the largest effect on the choice when to e-bike to work or not. Good weather, good cycling infrastructure, a low amount time, a shower present, secured parking present and financial support by employer present all have a positive effect on the likelihood to e-bike to work. On the other hand, bad weather, poor infrastructure, higher amount time, shower absent, safe parking absent and financial support by employer absent effect the likelihood of e-cycling to work negatively. We hypothesize that e-bike users are older and higher educated than the full sample of our investigation.

To answer all these questions and validate our hypotheses, we will do stated preference investigation. This allows us to know what factors the largest effect in the choice to e-bike have to work, without needing to ask what their most preferred factor is directly.

3 METHODOLOGY

3.1 Conjoint Analysis

The target of this thesis is to examine what is the effect of some contextual factors on the preference of people when e-cycling in commute. To do is we use an interview technique that tries to reveal the preference of the respondents. The used technique here is called ‘conjoint analysis’. This research methodology, introduced by Green and Rao (1971), allows us to understand what variables have the largest impact in a choice for a product or scenario. The aim of a conjoint analysis is to reveal the importance of certain product attributes in motivating a consumer toward the choice for a specific product. To answer this question, rrespondents need to evaluate multiple times a holistic appraisal of attribute combinations called profiles that represent this product. Every profile has the same attributes, only the attribute levels differ between the different profiles. The responses to these questions/evaluations allows the researchers to know what variables have the largest impact for this product. Marketing research frequently uses this technique to know what characteristics of a new product of a company will work. The technique is not only useful for companies that produce products, even for policy makers and researchers it can be helpful to know how multiple elements affect a choice (Frühwirth-Schnatter & Otter, 1999; Hair *et al.*, 1998; Holmes *et al.*, 2003; Louviere, 1988; Louviere *et al.*, 2000; Timmermans, 1984).

An easy short example to show what we mean by ‘a profile’, ‘attribute’ and ‘attribute levels’ is the following. Two profiles of milk exist. The first profile represents milk that is biological and produced in Belgium. The second profile represents milk that is non-biological and made in France. In this example, each profile has the same attributes, namely ‘how it is produced’ and ‘where’. For the attribute ‘how it is produced’, the attribute levels are ‘non-biological’ and ‘biological’ and ‘Belgium’ and ‘France’ for the attribute ‘where it is produced’.

Furthermore, conjoint analysis is an analysis technique that gives an understanding of the real underlying preference of the population. This is why it is a so-called ‘stated preference analysis’. The stated preference discrete choice technique relies on respondents making choices over hypothetical products or scenarios. We ask the respondents to choose the ‘best’ alternative from among a set of profiles that are completely described by a set of attributes generated from an experimental design (Hicks, 2002), as we will see further. This technique allows us to know what product respondents most like without having to create this product in real life. The hypothetical part of the technique allows us to gather larger amounts of data than only looking at the current existing products or scenarios.

The counterpart of stated preference research is the research related to ‘revealed preference’. Techniques in this category use observations of actual choices made by people to measure preferences (Hicks, 2002). We do not use hypothetical products, only the real-life choices of respondents are the focus of this sort of research. This gives the advantage that this technique will be more realistic. Yet there are limits about the amount of data we can gather. In stated preference analysis, this is no problem because the profile does not need to exist in real life to have an estimate how a respondent might like it (Kroes & Sheldon, 1988; Louviere, 1988; Louviere *et al.*, 2000; Timmermans, 1984).

An important element in a conjoint analysis is gathering the data on the preferences of the respondents. Specific for a conjoint analysis this is done using a rating or ranking exercise of the different profiles. Several different ways exist to do this. A first possibility is asking the respondent to rank all selected profiles. They can rank their most preferred profile on the first place and the least preferred option last. Similar to the first possibility, is a ranking exercise with selected groups of profiles. When there are many respondents, it is possible to use the combined data of several respondents to make one overall ranking of all used profiles. The advantage of this option is that respondents only need to rank a smaller amount of profiles. The disadvantage here is that need of larger sample sizes to gather enough information on all profiles. A third option for the rating of preferences is using a rating scale. The respondents need to give a number between a range (e.g. between one and ten) for each profile to show their preference for each profile without having to rank them. The last option is using paired comparison. In this scenario, the respondents have to choose multiple times from two profiles which profile a respondent prefers most (Frühwirth-Schnatter & Otter, 1999; Institute for Statistics and Mathematics, n.d.).

The research question in a conjoint analysis is: “To what extent does each component (factor) contribute to the total utility of a product (or scenario)?” (Institute for Statistics and Mathematics, n.d.). With a conjoint analysis, it is possible to derive the importance and preference for the attribute features and levels from the trade-offs made when selecting or ranking one of the available profiles over others, i.e. the results of the ranking or rating exercise. The metrics partial utilities of the different variable levels (called ‘part-worths’) from the ranking results allow researchers to know what hypothetical product or scenario has the highest (or lowest) utility (Louviere, 1988; Hair *et al.*, 1998; Qualtrics, n.d.).

We can reach those results by assuming that the utility that individual ‘i’ obtains from alternative (i.e. profile) j = 1 to J can be written as $U_{ij} = V_{ij} + \varepsilon_{ij}$, where V_{ij} is the deterministic part of the utility that depends upon observable characteristics (i.e. the variables and variable levels) and ε_{ij} is the random part. Individual ‘i’ chooses the profile ‘j’ if $U_{ij} > U_{ik}$ for all $k \neq j$. When we look closer at the deterministic part V_{ij}, more information is useful since this is the only part we can estimate. V_{ij} is equal to the dependent variable y that represents the preference of the interviewed person for the fictive products/scenarios. When we transcribe y, this becomes equation (1):

$$\mathrm{y} = \sum_{n}^{1} \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n \qquad (1)$$

In equation (1), β_n represents the coefficient, i.e. the estimated part-worth, for variable level X_n. The different variable levels X_n are here the independent variables (predictors). We can compute the utility structure of a number of persons using the aggregation of the single results of the respondents. Once we specify the distribution of ε_{ij} and the nature of the observable output decision, we can use a *probit* model in order to estimate the parameters of the behavioural process and the probability of choosing some alternative (Hair *et al.*, 1998; McFadden, 1974; Sarrias, 2016).

Doing a conjoint analysis comprises multiple steps. The first step is characterizing the decision process, next is identifying and describing the attributes and attribute levels. Then we develop an experimental design of the profiles, thereafter we will develop a questionnaire and the collection of data can happen. The penultimate step is determining the estimating model and the last step is interpreting the results for policy analysis or decision support (Aizaki & Nishimura, 2008; Hair *et al.*, 1998; Holmes *et al.*, 2003; Kroes & Sheldon, 1988; Lannoo *et al.,* 2018).

3.2 Decision process

In this part, we will give more information on what steps we will take to gather data and information in this conjoint analysis. As stated before, the first step is characterizing the decision process of this specific conjoint analysis. As we have seen, ‘conjoint analysis’ is a name for several stated preference techniques based on rating exercises. In this analysis, we can only use one of the possible rating possibilities. In this case, we choose the last option, i.e. the one where the rating happens based on paired-comparison of the profiles. This is more commonly known as the choice-based variant of conjoint analysis, i.e. choice-based conjoint (CBC). This technique, also known as discrete-choice conjoint analysis, is the most common form of conjoint analysis. A CBC requires the respondent to choose multiple times their most preferred full-profile scenario when two or more of those profiles are set next to each other. Each profile consists of the same variables, but has slightly different levels (Hair *et al.*, 1998; Kroes & Sheldon, 1988).

In this CBC, we do not wish to find the most important variables and variable-levels of a product, but from a scenario. This is in our case the commute with an e-bike. This will evidently affect the choices of variables and variable-levels. These will be linked to the hypothetical options that exist when people e-cycle to work. We can do this because when confronted with alternative travel modes, consumers will make decisions “on the basis of the terms upon which the different travel modes are offered, i.e. the travel times, costs and other service attributes of the competing alternative traveling modes”. An individual will select the mode that maximize his or her utility (Khan, 2007; Te Morsche *et al.*, 2019; Timmermans, 1984).

We choose to use a CBC over other conjoint ranking options because it is the most common form of a conjoint analysis and because answering choice questions is relatively similar to what people do when making choices or purchasing products in the real world. We also want to have information on average utilities and we do not need data on individual level. These different factors made us decide to use a CBC (Johnson & Orme, 1996).

3.3 Attributes

After the characterization of the decision process, we need to choose the attributes. A key issue here is to choose attributes that truly affect preferences. If we do not fulfil this command, this will heavily affect our results (Hair *et al.,* 1998). Important elements for the choice of attributes (and further attribute levels) are: relevance, interference, independence, compensatory relationships and having no exclusion criteria (Institute for Statistics and Mathematics, n.d.).

The number of attributes in a CBC has a certain limit. In a utopian world, every possible variable and level related to e-cycling to work, should be in the profile. In reality, this would create very larges profiles that are very hard for respondents to choose from and give insignificant results. The upper limit of number of variables is ten for a CBC (Sawtooth, 2017). Here we choose to use only seven attributes.

We determined these attributes using the academic literature on this topic applied on the Flemish context. Furthermore, we did three interviews with an e-bike retailer on what elements they discuss with potential e-bike buyers. The retailers put most emphasis on weight, type, location of battery, breaks and the type of e-bike. They did no provide information to customers in what situations e-bikes are useful.

As we have seen in the literature study about commuting, multiple elements affect e-bike commute. We can put those in different categories. A first one is ‘trajectory during commute’. Possible variables here are the infrastructure (presence of bike lanes or bike paths) and condition of the infrastructure, weather, time of day, trip time and the distance of the commute trip. Another category links with what is available at working place. These variables are the presence of a bicycle allowance, shower and (secured) parking. When we look at the characteristics of the e-bike we can distinguish the following attributes: a certain type/model of e-bikes (normal e-bike versus speedelec), speed (linked with time and type of e-bike), price of e-bike (in purchase), brand of e-bike, battery location, battery whether or not demountable, guaranty, weight and suspension among others. We cannot specify some variables in one category like environmental impact, trip purpose, and variables related to other transport modes like e.g. crowdedness and quality of public transport, car congestions or prize of car parking.

The seven attributes that we will investigate here are as discussed before (i.e. 2.13); time, bike trajectory, weather conditions, type of e-bike, availability of a shower at workplace, availability of a secured parking at workplace and financial intervention by the employer. We choose these attributes because of different reasons, as we will discuss below. Evidently there are some interrelations between the different attributes as we will see further.

3.3.1 Trip time

This attribute is one of the essential factors that affect commute. Not including this factor would lead to unrealistic profiles. We need to make a choice between the related factors distance and time for this variable. Including the two of them would lead to unrealistic profiles (e.g. a distance of 15 km combined with a trip time is 15 minutes, what would imply an impossible speed of the e-bike of 60 km/h). Since the e-bike is a means of transport with fixed transit times according to Rotthier and Cappelle (2017), we prefer to use time rather than distance.

3.3.2 Bike trajectory

The second attribute considered in this analysis is trajectory or infrastructure. We choose this element for several reasons. The first reason relates with policy goals. The Flemish government wants to invest in infrastructure for bikes. As we have seen before the government has the aim to realize a modal shift to 40% for sustainable modes in commute. Furthermore, for e-bikes trajectory is very important and evidently linked with safety. Enhancement in infrastructure have a positive effect on cycling to work (Buehler & Pucher, 2012; Howard & Burns, 2001; Mertens *et al.*, 2016; Mueller *et al.*, 2018; Nematchoua *et al.*, 2020; Stewart *et al.*, 2015; Rotthier *et al.*, 2017; Vanoutrive *et al.*, 2009; Wooliscroft & Ganglmair-Wooliscroft, 2014). Lopez *et al.* (2017) found that e-cyclists use cycle ways on average more than regular cyclists do. To understand how large the impact of infrastructure is on the choice to commute to work by e-bike, we chose this variable.

3.3.3 Weather conditions

The academic literature on commute shows that weather conditions have a large impact on when cycling to work. Is this impact similar for e-bikes? Excluding this from the profiles would lead to a lower form of realism in this study (Lopez *et al.*, 2017; Nematchoua *et al.*, 2020; Sears *et al.*, 2013; van den Bergh *et al.*, 2018). Flynn *et al.* (2012) found that increase in temperature and absence of rain has a positive effect on the likelihood of bicycle commuting. Increase in wind speed, presence of rain, snow has a negative effect on this likelihood. We will investigate if this similar for e-cycling in commute.

3.3.4 Type of e-bike

This variable considers the different variations within types of e-bikes. Knowing what sort of e-bike is most preferred can help policy decisions what investments have the highest priority. Rising sales numbers show that an enlarging audience accepts regular e-bikes. Is this similar for speedelecs or is there a clear difference between the preferences between these two options.

3.3.5 Availability of a shower at workplace

Beside the factors that affect the 'trajectory' when e-cycling to work, the facilities at the working place, may also have an effect. One of these facilities that we will consider here is the presence of a shower. Although e-cycling requires less effort than a regular bike, there still is some effort (Abraham *et al.*, 2002; Heinen *et al.*, 2013; Stewart *et al.*, 2015). Will people riding an e-bike in commute, similar to bicycle commuters, want to refresh themselves using a shower?

3.3.6 Availability of a secured parking at workplace

Another facility at the workplace is having a secured parking. Research suggest that this is the most important facility for regular bicycles (Abraham *et al.*, 2002; Fietsberaad Vlaanderen, 2013; Heinen *et al.*, 2013; Heinen & Buehler, 2019; Stewart *et al.*, 2015) and also rather important for e-bikes (Nematchoua *et al.*, 2020; van den Bergh *et al.*, 2018). The higher price of e-bikes affects this need. Is this suggestion also correct for e-bikes and how important is having a secured parking relatively to the other six alternatives in this investigation?

3.3.7 Financial intervention by the employer

The institutional framework tries to financially support and stimulate (e-)cycling to work. We have discussed the mileage allowance and the financial support when leasing a speedelec. Is there an additional role by the employer to stimulate e-cycling (De Tijd, 2018; IMOB, 2020; Stewart *et al.*, 2015; Vanoutrive *et al.*, 2009; Wardman *et al.*, 2007).

3.4 Attribute levels

For a CBC, we do not only need the attributes, but more important, we also need the attribute levels. Those make up the different profiles that respondents need to answer. We will give each of these attributes, multiple levels. Establishing the most appropriate value for each level will give the most correct results (Hair *et al.*, 1998). While the ranges of the variables need to be simple (LaVielle and Jeavons, 2012). We can determine the variable levels more precisely, in accordance with what is logical and feasible. Table 1 shows the used levels. Five attributes have two levels and two attributes (i.e. time and parking) have three levels.

Table 1: Variables and variable levels for conjoint analysis

Attribute	***Level 1***	***Level 2***	***Level 3***
Trip time	15 minutes	Between 15 and 30 minutes	30 minutes
Trajectory	Mostly cycling paths	Mostly along car roads	
Weather conditions	Good; dry and not windy	Bad; wet, windy	
Type of e-bike	Normal e-bike (speeds up to 25 km/h)	Speedelec (speeds up to 45 km/h)	
Shower at workplace	Present	Absent	
Secured parking at workplace	Present, *with* possibility to load battery	Present, *without* possibility to load battery	Absent
Financial intervention by the employer	Yes	No	

3.5 Experimental design

Once the attributes and attribute-levels are determined, we can construct those in specific combinations, i.e. ‘profiles’. These we can use later in the questionnaire, to do an attempt at understanding the respondents’ preference structure. Knowing this structure is the main goal of this investigation, because: “The preference structure depicts not only how important each factor is in the overall decision, but also how the differing levels within a factor influence the formation of an overall preference (utility)” (Hair *et al.*, 1998 p. 286).

The construction of those profiles is essential to go further in this analysis. E.g. in ‘profile one’ every variable level is set to a value of one. This creates a profile that consists of the following characteristics: time trajectory is around fifteen minutes and is mostly on cycling paths. The weather is nice, dry and not windy; riding on a normal e-bike (limited to 25 km/h). At the working place, a shower and a parking space for bikes with possibility to charge the battery of your e-bike are present; there is also financial aid of employer. Profile two is exactly the same, only the time of the trajectory has changed from ‘around fifteen minutes’ to ‘between fifteen and thirty minutes’. Every profile is every time a little different from the previous profiles. This continues for all the possible profiles. In total, this leads to 288 (= $2^5 * 3^2$) options. We call this the full factorial design. Showing all the possible profiles of the seven attributes and different levels to the respondents is not preferable. This number is too large and it would make the questionnaire too long.

A solution to this problem is only asking a partial set of factors. This is the 'fractional factorial design'. This design allows us to reduce the number of options, while remaining significant (Hair *et al.*, 1998; Kessels *et al.*, 2017; Timmermans, 1984). The fractional factorial design enables us to study simultaneously the effects of several factors. The maximum number of CBC-questions to ask before the respondents get bored or fatigued and want to end the survey is around twenty trade-off questions (Institute for Statistics and Mathematics, n.d.; Johnson & Orme, 1996; LaVielle & Jeavons, 2012). In academic literature, the minimum number of profiles is determined with the following equation: "minimum number of profiles = total number of levels across all factors – numbers of factors + 1". In this case, this leads to a least ten profiles (= 16 – 7 +1) (Hair *et al.*, 1998). This fractional factorial design is here set at sixteen (2*5 + 3*2). Here, we chose to ask more than those limited ten profiles. Obviously, larger samples than asking only ten profiles would provide a more accurate representation of the preference structure. Yet asking more than twenty profiles would result in indifference of the respondents (Hair *et al.*, 1998).

The next element that follows the determination of the number of profiles, is determining what sixteen profiles we choose from the full fractional design (the 288 profiles). We can do this randomly, yet this is not very common. It is more common to choose for a systematic selection. This will represent the full factorial design the best in a factorial design. There are two options in this case, a symmetric or an asymmetric design. For a symmetric design, all variables need to have the same number of levels. This is not the case in this investigation, five variables have two levels and two have three levels. Therefore, we choose here to do an asymmetric design. A possibility for the construction of reduced asymmetric design is using the pre-made "basic plans" of Addelman (Addelman, 1962; Institute for Statistics and Mathematics, n.d.). We choose not to use those readily available tables since they are not optimal in statistical sense (Zwerina *et al.*, 1996).

In this analysis, we prefer to make our own fractional design. We choose to use the Fedorov algorithm that selects the optimal selection from the full factorial design. This algorithm will select those sixteen profiles that represent best the full set of profiles in a CBC. We choose this algorithm over other options because it generates a D-Optimal design. Those designs are constructed to minimize the generalized variance of the estimated regression coefficients (Hintze, 2007; Miller & Nguyen, 1994).

The disadvantage of this algorithm is being time-consuming for larger data sets. This is not so much the case here because our dataset is rather small (288 * 7). Here, we apply the Fedorov algorithm in the programme RStudio, using the AlgDesign package, and the function 'optFederov()'. This function calculates an exact or approximate algorithmic design using the exchange algorithm of Fedorov (R-bloggers, 2009). Appendix A shows the used design code to create the choice-based conjoint design (Aizaki & Nishimura, 2008; Fedorov, 1972; Johnson & Orme, 1996; Johnson *et al.*, 2013). Table 2 shows the fractional factorial design with the sixteen selected options.

Table 2: Sixteen selected profiles

Profile	Time	Trajectory	Weather	Type	Shower	Parking	Financial
20	2	1	2	2	1	1	1
24	3	2	2	2	1	1	1
39	3	1	1	2	2	1	1
62	2	1	1	2	1	2	1
77	2	2	1	1	2	2	1
85	1	1	1	2	2	2	1
96	3	2	2	2	2	2	1
119	2	2	2	2	1	3	1
160	1	2	1	2	1	1	2
162	3	2	1	2	1	1	2
201	3	1	2	1	1	2	2
203	2	2	2	1	1	2	2
215	2	2	2	2	1	2	2
223	1	1	2	1	2	2	2
246	3	2	1	1	1	3	2
273	3	1	2	1	2	3	2

Once we select the sixteen profiles with the Fedorov-algorithm, we need to create the questions for the respondents. In the questionnaire, we will ask each profile twice, each time compared with another profile. This creates evidently sixteen questions. Each profile is once option A, and once option B in a question. To select a random order of profiles, we use RStudio. Appendix A shows how to do this. Once the choice-set is created, we need to check it visually for doubles. This is necessary to make sure no question had the same two profiles or to avoid a certain question had the same two profiles than another question (and only the profiles switched position). Table 3 shows the full choice-set for the sixteen questions. We see e.g. that profile 223 is once profile 1 (i.e. in question 1) and once profile 2 (i.e. in question 12).

Table 3: Choice set

Number CBC question	**Profile 1**	**Profile 2**
1	223	215
2	119	246
3	96	24
4	246	203
5	24	20
6	201	139
7	160	273
8	62	85

Number CBC question	Profile 1	Profile 2
9	39	160
10	203	77
11	85	119
12	20	223
13	77	162
14	273	96
15	162	201
16	215	62

Additional to each set of two profiles, we give the possibility to the respondents to choose a none-of-these alternative (i.e. the option to travel by 'any other mode than an e-bike'). We gave this additional third alternative for several reasons. First, it offers the respondents a way-out when it is hard to decide when the two alternatives or similar bad or good in their eyes. It also offers the option when they do not, whatever alternative; want to e-bike to work (Johnson & Orme, 1996; Kessels *et al.*, 2017; Lannoo *et al.*, 2018; Zijlstra, 2016). Being able to respond 'none-of-these' also helps to retain realistic conditions in these choice-simulations (Hair *et al.,* 1998; Peruzzi *et al.*, 2015). According to Johnson and Orme (1996), there are two hypothesises to choose for the none-option. The first one relates to the fact that neither of the options offer sufficient attractiveness. We call this the 'economic hypothesis'. The other hypothesis is the 'decision avoidance hypothesis'. The latter relates, as the name already suggests, that the two options are similar (dis)attractive for a respondent and he can avoid making a decision.

3.6 Survey design

After the creation of the experimental design of the CBC part, we transfer this design into a questionnaire. This way, respondents can fluently fill in this questionnaire and makes it possible to ask additional information beside the CBC part. For this purpose, we use the statistical survey web application Lime Survey. We use this programme to create the survey and respondents can answer as well in this programme. We used this survey software for numerous reasons. First, it is free to use and easily accessible. This kept the threshold for completing the survey as low as possible. The software allows showing the number of total questions in the beginning of the survey. Another advantage of the software is the possibility to show the progress at the respondent at the top of the page. Those elements give an estimate to the respondent how long it will take to complete the survey. It helps convincing respondents to continue and end the survey. We asked the questions in Dutch; we did this because the target group of this investigation was commuters in Flanders.

The design of our survey had a specific order. The idea behind this is to retain respondents' attention as high as possible during the questionnaire (Harvard University Program on Survey Research, 2007; Pew Research Center, 2020). The survey started with multiple questions about the commute of the respondent. Those questions relate to postal code of work, postal code of home, trip time, trip distance and most used mode in commute. After this, the main part of this survey followed. This part started with an explanation about CBC. This contained information about the scenario ("Imagine you would do your commute with an e-bike, what alternative would suit you most?") and we presented an example of a CBC-question with two possible profiles. Additionally, we gave information to the respondent that it is possible to select the none-of-these option. After this explanation, the sixteen CBC-questions followed, we split those in two groups of eight questions. At each question, respondents need to make a choice between three different options (two profiles and none-of-these alternative).

After this, we asked a first set of control questions. These questions related to the different factors that made up the profiles of the CBC. Each question had the same structure, in this case: "Does <variable> play a role in your mode choice in commute?". After those questions, we asked multiple demographic-related questions. These included questions on age, gender, highest degree, e-bike ownership, willingness to own an e-bike, willingness-to-pay (WTP) for an e-bike and a question that asked what other factors do play a role in (e-bike) commute.

After these seven questions, the second set of control questions followed. These also related to the variables of the CBC. Yet, they asked the same question of the first set in a slightly different manner. In this second set, the control questions were each time formulated as followed: "Is <variable> a determining factor in your mode choice in commute?". The purpose of those two sets of control questions is to have a way to clean the dataset afterwards. If a respondent answers frequently different to two similar questions, he most likely did not fill in the full survey correct and truthful. The answers to these questions can also be useful to see if respondents are able to estimate themselves and see if one of the variables was more or less important for them.

In the final part of the questionnaire, we asked a question if they wanted to receive information over the results of this investigation. If they answered this positively, they could give their e-mail address in the following question. The final question of this survey offered the possibility to each respondent to give further comments and remarks on e-bikes in commute or this survey. After the respondent send in their answer, we thanked the respondents for completing this survey. Appendix B shows the full survey.

The goal is to make a survey that is not too long to answer, so there is a bigger willingness to answer the questionnaire. Once that survey design was finished, ten hypothetical respondents (i.e. friends and family) pre-tested the survey. They could give some feedback on the survey and allowed to give an estimate time to fill in the survey at future respondent. After consideration of this feedback and making some adjustments, the survey was ready for other respondents.

The estimated time of filling in the full questionnaire is around 10 minutes. This is in line with the good practices and tips from about surveys with conjoint analysis. Johnson and Orme (1996) found that the needed time to fill in one CBC-question is around 12 seconds. Answering the first question takes the longest. After the first number of questions, this stabilizes around 12 seconds. We can conclude that answering the CBC-part of the questionnaire with sixteen questions will take on average slightly over four minutes (16*12 seconds) and the other questions around 6 minutes. Afterwards, we can download the answers/results of the survey and analyse them in other programmes, as we will see further

3.7 Collecting data

The data collection happened in March 2020 (between 09 and 24 of March). To reach out to a maximum amount of respondents, we took several initiatives on social media. We did an outreach asking people to fill in the survey on Facebook, Twitter, Strava and LinkedIn. The target audience were commuters in Flanders.

To have an idea how many respondents are needed (i.e. the needed sample size) for a CBC, a rule-of-thumb exists:

$$\frac{n * t * a}{c} > 1000 \tag{2}$$

In equation (2), n = number of respondents, this is equal to the sample size, t = number of tasks, a = the number of alternatives per task, C = the largest number of levels for any one attribute. In this case t = 16, a = 2, C = 3. This makes, when transforming this formula that n needs to be higher than (1000*c)/(t*a). In this case n > 93 (Johnson *et al.*, 2013; LaVielle & Jeavons, 2012). This makes that at least 94 people need to fill in the survey. This is line with other statements on sample size for a CBC. Hair *et al.* (1998) consider samples sizes ranging from 50 to 200 as adequate. Obviously, larger samples would provide a more accurate representation of the population of interest. A minimum of 100 respondents should lead to significant attribute scores in our analysis.

3.8 Data cleaning

Before going over to the analysis of the results, we download the survey results to an Excel-file. This allowed us to clean the data. We controlled the answers of the respondents on multiple elements. Firstly, we use the control questions for this purpose. We also used the needed time to fill in the survey and controlled respondents who showed some 'straight lining'. This is choosing the same answer option repeatedly (e.g. the first answer option) (Qualtrics, 2018).

Respondents that answered more than two control questions differently or filled in the survey very fast (the bar is here set at five minutes) and showed some 'straight lining' were put apart. We will control if they really mess up the data and did not fill in the survey honestly. To control this, we will see if including them or not in the model influences the results. If the results look similarly without them, we will exclude them from further analysis and results. If there is a clear difference, we will do further analysis using Markov Chain Monte Carlo methods (Robert & Changye, 2020).

3.9 Estimating model

After the data cleaning, the interpretation and analysis of the survey answers could start. For this purpose, multiple models are possible. In this analysis, we chose to use a *binary logistic regression* including the none-of-these option or also called a *no-choice binomial logit model* (Haaijer *et al.*, 2001). This model will allow us to analyse the choices of the respondents. We choose this model for several reasons.

The first reason to choose for this model is that our dependent variable is dichotomous (yes or no, 1 or 0). In our case, the preference of the interviewed person for the fictive products/scenarios. A respondent likes a profile or not. There are only two options for a respondent. Either a respondent chooses for a certain alternative, this gives this alternative a value of '1'. If a respondent does not choose for an alternative, this gets a value of '0' (McFadden, 1974; Hosmer & Lemeshow, 2000).

A second reason why we choose this model is that we want to know the importance of the different variables and variable levels. A logistic regression estimates the coefficient of the different factors that we combine in a profile. Having those coefficients helps us to determine what factors have the largest influence on a respondent's choice for a factor. It even allows us to determine what profile has the highest preference and what profile the lowest. Furthermore, we can also estimate what is the likelihood of the none-of-these option (Hauber *et al.*, 2016; Hosmer & Lemeshow, 2000; Lannoo *et al.*, 2018). A third reason to choose this no-choice binomial logit model was because it allows us to include the none-of-these option. This makes it easier to estimate the coefficients and gives a better predictive fit than when we would not include this no-choice option or use a nested logit model (Haaijer *et al.*, 2001; Lannoo *et al.*, 2018).

Another advantage of using the logistic regression is that we can split up our data in two groups and determine if there are differences between two groups. We can for instance split the data in two groups based on gender, age and e-bike ownership. For each group we can calculate the coefficients of each group and control if the results really differ (cf. 3.11 for more detailed information).

3.9.1 Logistic regression

Since we choose to do a logistic regression, more information on this analysis is useful. The goal of a logistic regression model is to know the relationship between the explanatory variables and the dependent variable. In our analysis we also want to know what the link between the alternatives and alternative levels is (= the explanatory variables or independent variables) and the choice for a certain profile (= the dependent variable). In a logistic regression, the independent x-variables are used to build a mathematical equation that predicts the probability that the dependent y-variable takes on a value of '1'. Thus, we use logistic regression when it is plausible that whether the *Y*-variable is 0 or 1 (Hauber *et al.*, 2016; Hensher & Johnson, 1981; Hosmer & Lemeshow, 2000; McFadden, 1974).

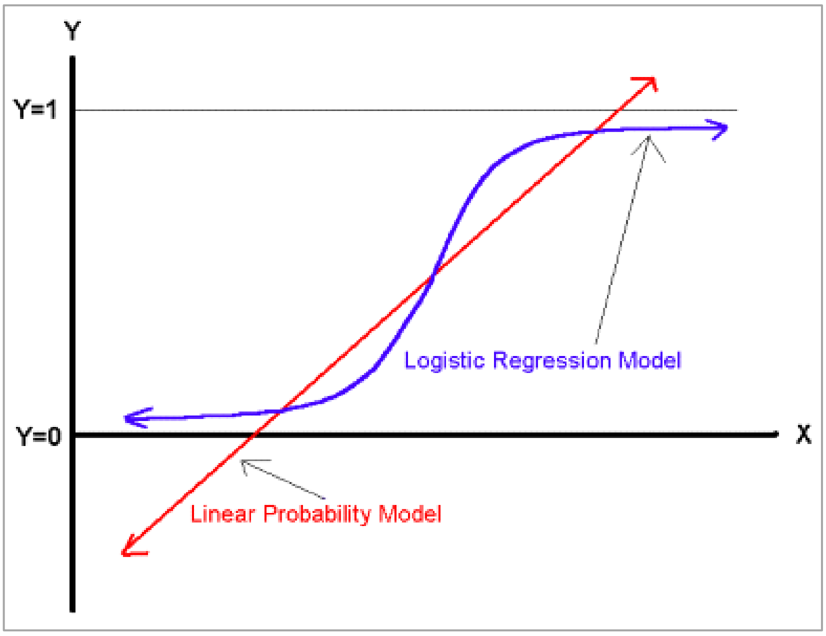
A logistic regression determines the chance a respondent chooses a certain alternative, while using the log of the odds ratio. It follows this equation:

$$\ln\left(\frac{p}{1-p}\right) = y = \sum_{n}^{1} \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n \quad (3)$$

In equation (3): $\frac{p}{1-p}$ is the odds ratio, p is the probability that a respondent will choose an alternative with certain characteristics (i.e. a certain profile), β_n are the different coefficients for the different variable levels X_n. We can transform this equation to the following form:

$$p = \frac{e^y}{1+e^y} = \frac{1}{1+e^{-y}} \quad (4)$$

Having this transformed equation (4), allows us to calculate the probability of a certain profile. This probability is in our analysis equal to the likelihood a person e-bikes to work (given those characteristics). Graph 5 shows the formula of logistic regression graphically. We see that it will give us a value between 0 and 1, the probability of a profile.



Graph 5: Logistic regression and linear probability model (Sayad, n.d.)

Specific in this analysis, we adapt this basic formula to the following equation for y:

$$\begin{aligned} Vj \ = \ & \beta_G * Time\ 15\ min_j + \beta_H * Time\ between\ 15 - 30\ min_j + \beta_K * Trajectory_j + \beta_L * Weather_j \\ & + \ \beta_N * Type_j + \beta_M * Shower_j + \ \beta_N * \ Parking\ with\ chargepoint_j + \beta_O \\ & * Parking\ without\ chargepoint_j + \beta_P * Financial\ support_j + \beta_Q * None_j \end{aligned} \quad (5)$$

To translate the categorical variables in our profiles from our experimental design in the questionnaire to a data frame for the analysis, we use here a hybrid form of coding. This is a combination of dummy coding and effects-type coding. The categorical variables with two levels are translated using effects-type coding and those with three levels (parking and time) with dummy level coding (Cooper *et al.*, 2005; Hensher *et al.*, 2005). Appendix C shows the translation of all the profiles to a data frame for one respondent.

We could upload this data frame in SPSS. In this statistical programme, we could carry out a logistic regression, using Analyze > Regression > Binary logistic.

3.10 Interpretation of the results

The output of the logistic regression in SPSS consists of several results. The main results of the estimating model are the estimates of the coefficients, i.e. part-worths. These will give us information what variable and variable level have the largest impact on the choice for a certain profile. Based on the coefficients of the calculated variable levels, we can calculate the chance a respondent chooses a certain alternative. Since we already know the coefficients of the variable levels, we can further calculate this value for the reference levels.

For the variables with only two levels, the reference level is equal to minus the calculated level for that variable, since we use effects-type coding. For the variable with three levels that are dummy coded, the reference level is equal to zero.

To know if a part-worth is significant in our model, we use a Wald test (or Wald Chi^2 test) for the different variable levels. This allows us to compare for each variable level if including this variable level in the model has an effect or no, hence we compare our model with a null model (all part-worths are equal to zero). In the output, we can we can determine the significance of a variable using the p-value for each variable level. This *p*-value or probability value beholds the lowest α-value at which we still reject the H_0-hypothesis. The α-value is the chance of doing a type I error. This error beholds rejecting the H_0-hypothesis, while this is in reality correct. We want to have a very small chance to make this error; therefore, we want to have a low α-value and linked p-value.

The hypotheses for H_0 and H_A in a Wald-test are the following: H_0-hypothesis is: the two coefficients of interest, the coefficient of our model and of the null model, are simultaneously equal to zero, this implies that there is **no** effect for this variable (or variable-levels) in our model; the means of the two models is the same. The H_A-hypothesis is: the two coefficients of interest are not simultaneously equal to zero, this means that there is **an** effect for this variable (or variable-levels) in this model; the means of the two models is different from each other'. Evidently, we hope to reject the H_0-hypothesis and accept the H_A-hypothesis. Therefore, the α-threshold needs to be as low as possible. In the results, we can only see the p-value. We want this to be as low as possible to be able to reject the H_0-hypothesis. We set the cut-off at 0,05. The *p*-value of a variable level needs to be lower than 0,05 to be seen as significant. This will give us a 95% certainty that we will not make a type I error (Fox, 1997; Johnston & DiNardo, 1997; Van Messem, 2014). The variables with a p-value higher than 0,05 are insignificant in our model.

Once we checked the significance of the different part-worths, we can check the coefficients itself. First, we can calculate the reference level as stated before. If a part-worth has a positive sign, this affects the chance of a profile containing this attribute level positively. If it has a negative sign, the chance of a profile with this attribute level is lower. Furthermore, we can determine what variables will have the highest preference. Similarly, we can determine the least preferred profile. We can also calculate the likelihood of the 'none-of-these option' and the importance of the different attributes.

We can calculate the relative importance of each attribute by dividing the Wald score of a variable by the sum of Wald scores of all variables We can do this since the higher Wald the more important a factor is and the smaller the Wald value, the less important a factor it is. We have to compare variables this way, since we cannot compare utility scores across attributes but only consider them relative gauges of level preferences within each attribute (Peruzzi *et al.*, 2015).

To check how good our full model is in explaining the answers of the respondents, we can use multiple elements. The first one is a classification table. This table compares the predictions of our model with the observations (i.e. the answers of our respondents). The more predictions of our model are correct the better our model. Furthermore, we can interpret the log-likelihood ratio. The interpretation of the log-likelihood is as followed: it lies between -∞ and zero. The closer the log-likelihood is to zero, the better the model explains (fits) the data, and thus the better our model.

Additionally, we can also determine the goodness-of-fit of our logit model. We can do this by checking the R^2 of the model. Although the R^2-values of a logistic regression will be lower than in linear regression, it is useful to check this value. Multiple ways exist to do this; there is no consensus on what option is best for a logistic regression. The SPSS output will give us the Cox & Snell R^2, Nagelkerke R^2 and the -2-log likelihood. Furthermore, we can use the Hosmer-Lemeshow goodness-of-fit test to determine the goodness-of-fit of our logistic regression. It tests how good the observed events match with the expected events (Hauber *et al.*, 2016; Hosmer & Lemeshow, 2000).

We can do the analysis of the non-CBC related questions using Microsoft Excel. This allowed us to calculate the means, standard errors and sums. We applied this on time to fill in questionnaire, age, gender, education-level, commute trip distance and - time, e-bike ownership, willingness to own an e-bike, WTP for an e-bike and stated importance of variables (i.e. the control questions). For the analysis of the question 'other variable that effect e-bike use', we could count the number of times a variable was stated.

3.11 Comparing two groups of coefficients

After we checked the results of the logistic regression, we can do some more analysis between different groups in the respondents. For this purpose, we split up the data in two groups based on user characteristics and calculate a logit model for the two groups. Once we did this, we can check the coefficients of the two groups for similarities. To see if the differences between the groups is significant, we use the following equation for each coefficient:

$$Wald\ Chi\ square\ statistic = \frac{(\beta_A - \beta_B)^2}{(s.e.(\beta_A))^2 + (s.e.(\beta_B))^2} \tag{6}$$

In equation (6); β_A is the coefficient for group A for a certain part-worth, β_B the coefficient for group B for the same variable level and *s.e*. for the estimated standard error. This statistic has one degree of freedom (2-1) and allows us to check the significance of each variable level.

When we find significant variable levels, we can go further in our analysis to see if this difference between the two groups is not due to residual variation (i.e. unobserved heterogeneity). To do this we can do a new logistic regression to see if the difference is not due to this residual variation. The equation for this logistic regression is the following:

$$y = \alpha + \sum \beta x_i + \gamma G_i + \delta(x_i \times G_i) + \varepsilon \tag{7}$$

In equation (7): α, β, γ, δ are the coefficients, x_i are the different variable levels, G_i is the interaction term (the characteristic of a group). This is a binary value that takes a one when a respondent is part of group A and zero when a respondent is part of group B. the $x_i \times G_i$ is the variable level that is significant multiplied with the G_i–value, we discussed before. When we calculate the coefficients of this model, we can see if δ is significant. If this is case, the differences between the two groups is not due to residual variation. When δ is non-significant, the coefficients of the variable level are similar (Hauber *et al.*, 2016; Allison, 1999). We will do this for the following groups; gender (male compared to female), e-bike ownership (e-bike owners compared to non e-bike owners), age (young compared to elderly people). For age, we split up the respondents based on average age of the full sample.

Furthermore, we will see if we can do this analysis based on location, to check if there exists a difference between respondents living in urban regions or in rural regions. We will split the data for this purpose in two groups based on postal code.

4 RESULTS

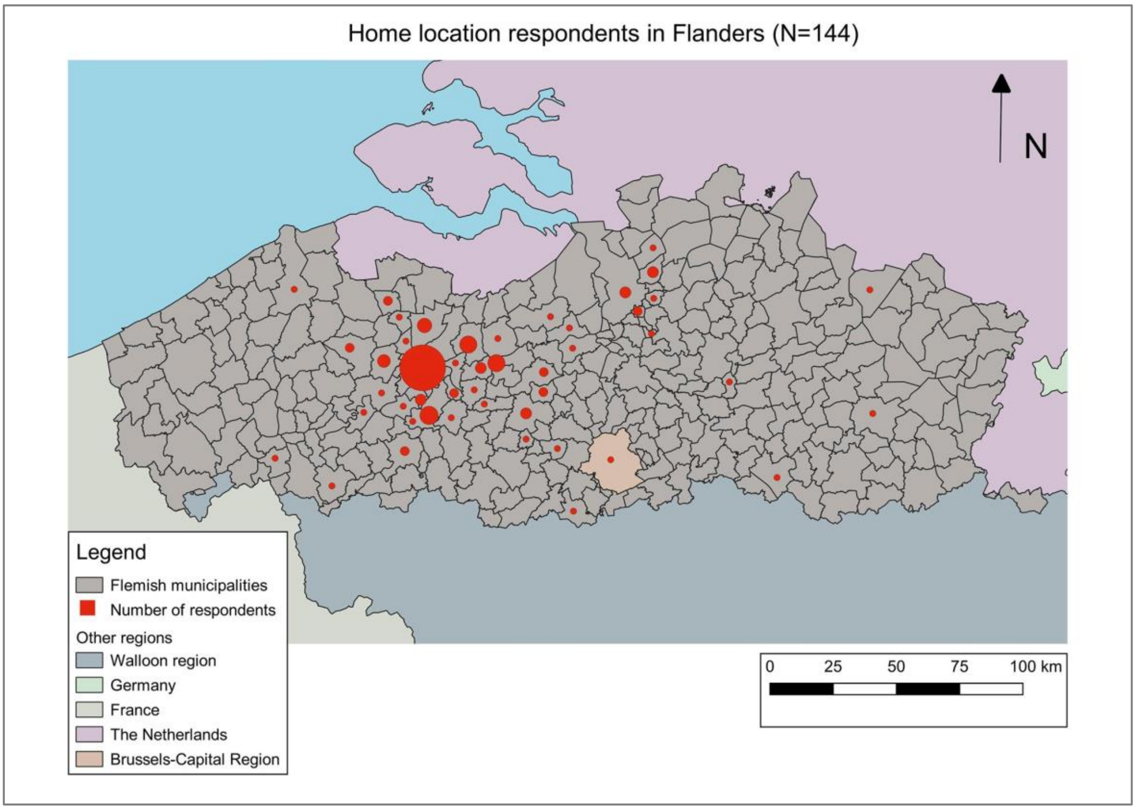
4.1 Respondents

After the survey ended, 154 respondents had filled in the full questionnaire. After data cleaning, this number was reduced to 144. Appendix D shows the results of the data cleaning. We saw no differences between including them or not, therefore as we discussed before (3.8), we will leave them out in further analysis. Table 4 shows the level variables for all respondents (including both e-bike owners and non e-bike owners) and separately for e-biker owners. Map 1 and 2 represent the home and work location of the respondents in Flanders.

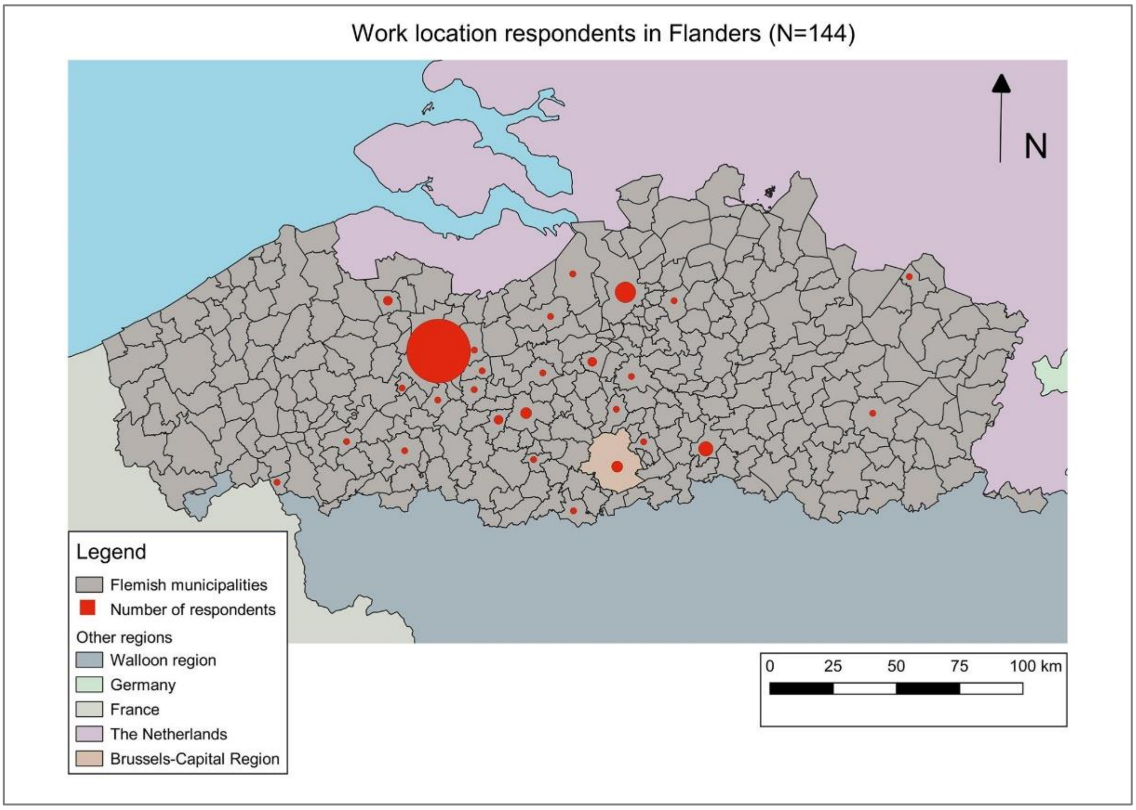
Table 4: Respondent level variables

Number of respondents	**144 (incl. e-bike-owners)**	**57 (only e-bike- owners)**
Time to complete survey	Mean: 13’00”; s.e.: 5’33”	Mean: 12’58”; s.e.: 5’44”
Age	Range: 18-59 Mean: 38,75; s.e.: 11,92	Range: 22-59 Mean: 44,38; s.e.: 9,53
Gender	41,0% are men 59,0% are women	33,3% are men 66,6% are women
Educational background **(highest obtained degree)**	13,9% have a high school diploma 39,6% have a bachelor’s degree 37,5% have master’s degree 7,6% have a PhD	8,8% have a high school diploma 36,8% have a bachelor’s degree 40,4% have master’s degree 10,5% have a PhD
Average commute trip distance	15,12 km; s.e. = 14,75	15,81 km; s.e. = 13,68
Average commute trip time	30’22”; s.e. = 19,31	31’41”; s.e. = 16,28

Modal share in commute	31,9% Car (as driver) 0% Car (as passenger) 9,7% Train 2,1% Tram 0,7% Bus 27,8% Bicycle 26,7% E-bike 0,7% On foot 0,7% Other	28,1% Car (as driver) 0% Car (as passenger) 5,3% Train 0% Tram 0% Bus 0% Bicycle 66,7% E-bike 0% On foot 0% Other
E-bike ownership	39,6% own an e-bike 52,8% do not own an e-bike 7,6% someone in family own an e-bike	100% own an e-bike 0% do not own an e-bike 0% someone in family own an e-bike
Future willingness e-bike ownership	38,2% already have an e-bike 13,9% want to acquire a regular e-bike (v < 25 km/h) 5,7% want to acquire a speed pedelec (v < 45 km/h) 13,9% want maybe to acquire an e-bike 28,5% do not want to acquire an e-bike	96,5% already have an e-bike 0% want to acquire a regular e-bike (v < 25 km/h) 3,5% want to acquire a speed pedelec (v < 45 km/h) 0% want maybe to acquire an e-bike 0% do not want to acquire an e-bike
WTP for an e-bike	Average = € 2312,49; s.e. = 1498,94	Average = €3 060,20; s.e. = 1546,80



Map 1: Home location respondents (Agentschap Informatie Vlaanderen, 2016; Eurostat, 2018)



Map 2: Work location respondents (Agentschap Informatie Vlaanderen, 2016; Eurostat, 2018)

4.2 Conjoint Analysis

4.2.1 Part-worths utilities

Table 5 represents the main results of the CBC. In total, we observe 2304 choice situations (144 respondents*16 CBC-questions). The table shows the part-worths of the variable levels and their standard errors, the Wald-statistic and the significance of each variable(-level).

Table 5: Results of the No-Choice binomial logit model

	Coefficient (= B)	Standard Error	Wald	DF	Significance (p-value)
Intercept	-0,649	0,083	61,79		0,000
Trip time			105,69	2	0,000
• **15 minutes** • **Between 15 and 30 minutes** • **30 minutes**	0,375 0,197 0	0,102 0,094			
Trajectory			60,82	1	0,000
• **mostly cycling paths** • **mostly car road**	0,280 -0,280	0,036			
Weather			237,15	1	0,000
• **Good (dry and not windy)** • **Bad (wet and windy)**	0,528 -0,528	0,034			
Type			102,76	1	0,000
• **Normal e-bike** • **Speedelec**	0,587 -0,587	0,058			
Shower			8,17	1	0,004
• **Present** • **Absent**	0,143 -0,143	0,050			
Parking			70,86	2	0,000
• **Present *with* possibility to load battery** • **present *without* possibility to load battery** • **Parking: absent**	0,802 0,042 0	0,112 0,098			
Financial intervention by employer			98,71	1	0,000
• **Present** • **Absent**	0,557 -0,557	0,056			
No-choice parameter	-0,817	0,098	69,08	1	0,000
Hosmer-Lemeshow = 27,921				7	0,000

We can already see some results in Table 5. All variables are significant, since all p-values are smaller than 0,05. If we check the sign of the different part-worths, we see that if time enlarges, the likelihood of a profile decreases. If the profile has ‘mostly on a bike road’, this increases the likelihood of this profile. Contrary, when it is ‘mostly on a car road’, the sign is negative (in this case -1* 0,280 = -0,280, i.e. effects-type coding). The same line of thinking works for all the other variable levels. If the weather is good, this has a positive effect. When the weather is bad this has a negative effect on the likelihood of profile. When the type of e-bike is a normal, this has a positive effect. If it is a speedelec, this has a negative effect on the likelihood of a profile. When a shower is present, this has positive effects on the likelihood, if a shower is absent has a negative effect on the likelihood of a profile. When looking at financial intervention by employer, we see that if present, this has a positive effect. If absent, there is a negative effect. The last variable level that need to be checked is ‘parking’. We see that if this is present with possibility to charge the battery, there is a large positive effect. When present but without charging possibility, this is very small. If no parking is present, the part-worth is zero (i.e. dummy coding). Furthermore, we can calculate the prediction table for our model, assessing the number of answers that it predicts correctly. Table 6 shows this prediction table. We see that 59,9% of the answers is predicted correctly. Table 7 represents the different goodness-of-fit tests.

Table 6: Classification table

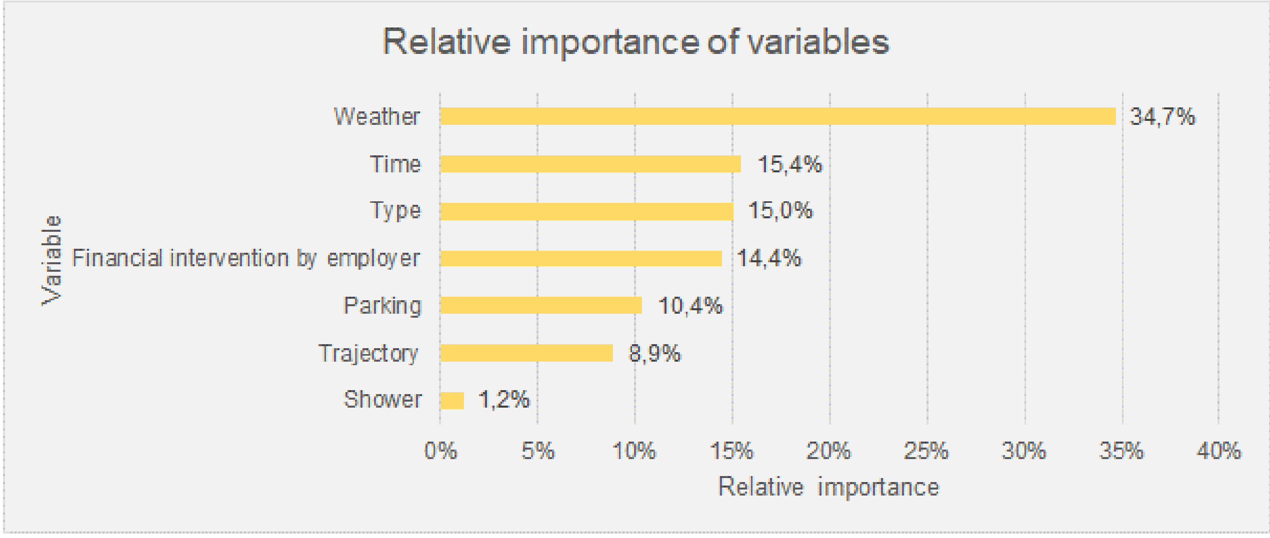
	PREDICTED RESPONSE: 0	**PREDICTED RESPONSE 1**	**PERCENTAGE CORRECT**
OBSERVED RESPONSE: 1	1850	1379	42,7%
OBSERVED RESPONSE: 0	2758	925	74,9%
OVERALL PERCENTAGE			59,9%

Table 7: Goodness-of-fit tests

	Cox & Snell R^2	**Nagelkerke R^2**	**-2*log-likelihood**
Score	0,133	0,184	7816,205

4.2.2 Variable utilities

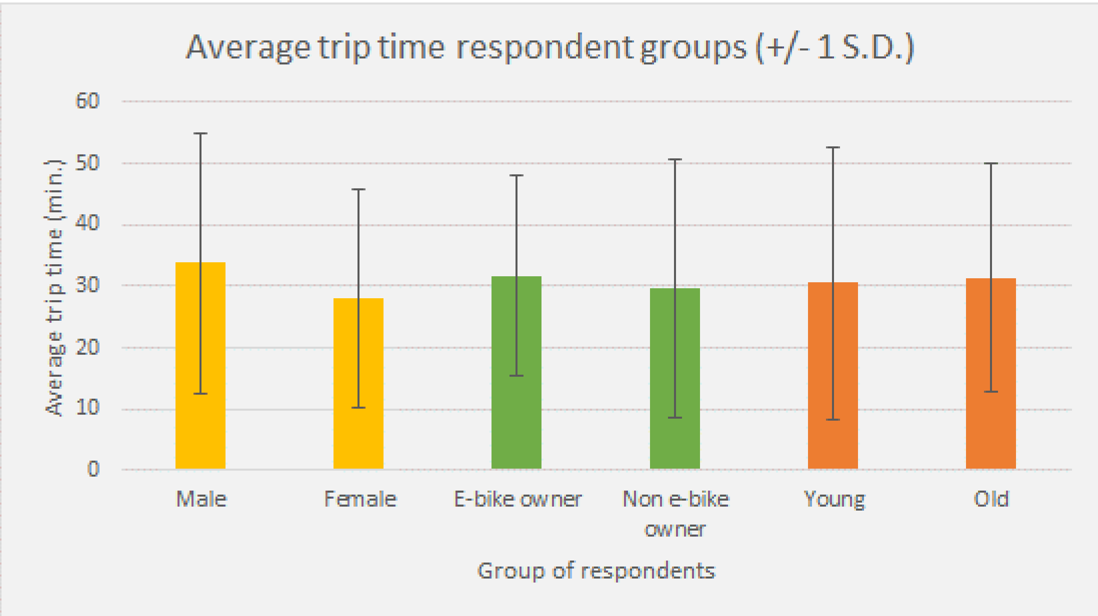
Furthermore, we can calculate the relative importance of each variable to see what the effect of this variable in a profile is. Graph 6 shows the results of this analysis.



Graph 6: Relative importance of variables

4.3 Specific role of user-characteristics

Beside the main results of our logit model, we could do further analysis using user characteristics of the respondents. Graph 7 shows the average trip time of the different respondent groups we investigate here.



Graph 7: Average trip time respondents (+/- 1 S.D.)

4.3.1 Gender

The first characteristics that we consider here is gender. Our dataset consists of 58 male and 85 female respondents. Table 8 and Appendix E show the results of this analysis. We see that for gender the variable-levels time is 15 minutes and type are significant, just as the none-of-these option.

Table 8: Effect of gender on variables

	B male	**s.e.**	**B female**	**s.e.**	**Wald Chi square stat.**	**Significant p-values**
Intercept	-0,96	0,055	-0,74	0,04	10,46486486	p<0,05
Time						
• **15 minutes** • **Between 15 and 30 minutes** • **30 minutes**	0 0,16 -0,16	0,11 0,06	0,32 -0,11 -0,21	0,09 0,07	5,069306931 0,221238938	p<0,05
Trajectory						
• **mostly cycling paths** • **mostly car road**	0,31 -0,31	0,06	0,27 -0,27	0,05	0,262295082	
Weather						
• **Good (dry and not windy)** • **Bad (wet and windy)**	0,52 -0,52	0,05	0,55 -0,55	0,05	0,18	
Type						
• **Normal e-bike** • **Speedelec**	0,38 -0,38	0,08	0,76 -0,76	0,08	11,28125	p<0,05
Shower						
• **Present** • **Absent**	0,23 -0,23	0,08	0,09 -0,09	0,07	1,734513274	
Parking						
• **Present *with* possibility to load battery** • **present *without* possibility to load battery** • **Parking: absent**	0,48 -0,23 -0,25	0,1 0,08	0,57 -0,25 -0,32	0,08 0,07	0,493902439 0,03539823	
Financial intervention by employer						
• **Present** • **Absent**	0,45 -0,45	0,08	0,66 -0,66	0,08	3,4453125	
No-choice parameter	-0,77	0,06	-0,57	0,04	7,692307692	P<0,05

4.3.2 E-bike ownership

Beside the effect of gender, we control the data if there are significant differences between e-bike owners (57 respondents) and non e-bike owners (87 respondents). Table 9 and Appendix F shows the analysis of the differences between the two groups. We see that only variable level type is here significant. If we do further analysis, controlling whether this is due to residual variation or not, we see that this is not the case. We see that only type is significant, all other variables are insignificant. We interpret here that when someone already owns an e-bike that the effect of a normal e-bike in a profile has a higher likelihood than when a respondent possesses no e-bike. Similarly, when a profile contains as type a speedelec, the likelihood of choosing this profile is lower when you possess an e-bike than when you do not own an e-bike. We can conclude that the possession of an e-bike makes you want more a regular e-bike than a speedelec.

Table 9: Effect of e-bike ownership on variables

	B e-bike	s.e.	B non e-bike	s.e.	Wald Chi square stat.	Significant p-values
Intercept	-0,82	0,05	-0,82	0,04	0	
Time						
• **15 minutes** • **Between 15 and 30 minutes** • **30 minutes**	0,2 -0,01 0,19	0,11 0,08	0,17 0,02 -0,19	0,09 0,06	0,044554455 0	
Trajectory						
• **mostly cycling paths** • **mostly car road**	0,28 -0,28	0,06	0,28 -0,28	0,05	0	
Weather						
• **Good (dry and not windy)** • **Bad (wet and windy)**	0,47 -0,47	0,05	0,57 0,57	0,04	2,43902439	
Type						
• **Normal e-bike** • **Speedelec**	0,77 -0,77	0,1	0,48 -0,48	0,07	5,644295302	$p<0,05$
Shower						
• **Present** • **Absent**	0,09 _0,09	0,08	0,18 0,018	0,06	0,81	
Parking						
• **Present *with* possibility to load battery**	0,53	0,1	0,52	0,08	0,006097561	

• **present *without* possibility to load battery** • **Parking: absent**	-0,23 -0,3	0,08	-0,24 -0,28	0,07	0,008849558	
Financial intervention by employer						
• **Present** • **Absent**	0,65 -0,65	0,09	0,51 -0,51	0,07	1,507692308	
No-choice parameter	-0,72	0,05	-0,6	0,04	3,512195122	

4.3.3 Age

Furthermore, we can do the same analysis for age. We have 73 respondents who are younger than the mean age of all respondents (= 38,8 years old) and 71 respondents are older. Table 10 and Appendix G show the result of this analysis. We see that the factors ‘weather’ and ‘financial aid by employer’ are significantly different between the two groups. When the weather is good, for both groups this affects significantly positive the likelihood of choosing a certain profile. Yet in the group of younger respondents, this has a larger positive effect than in group of older respondents. For financial support by the employer, we see a similar result. When there is financial support present, this effects the likelihood for the two groups positively, yet for the younger group, there is a significant larger effect than in the group of older respondents. Furthermore, there is also a significant difference between the two groups for the none-of-these alternative. The likelihood of choosing an e-bike when a respondent is older is higher than when a respondent is younger.

Table 10: Effect of age on variables

	B young	**s.e.**	**B old**	**s.e.**	**Wald Chi square stat.**	**Significant p-values**
Intercept	-0,86	0,05	-0,79	0,05	0,98	
Time						
• **15 minutes** • **Between 15 and 30 minutes** • **30 minutes**	0,36 -0,11 -0,25	0,1 0,07	0,02 0,1 -0,12	0,01 0,07	5,78 1,724489796	p<0,05
Trajectory						
• **mostly cycling paths** • **mostly car road**	0,28 -0,28	0,05	0,28 -0,28	0,05	0	
Weather						

• **Good (dry and not windy)** • **Bad (wet and windy)**	0,61 -0,61	0,05	0,45 -0,45	0,05	5,12	p<0,05
Type						
• **Normal e-bike** • **Speedelec**	0,66 -0,66	0,09	0,53 -0,53	0,08	1,165517241	
Shower						
• **Present** • **Absent**	0,15 -0,15	0,07	0,14 -0,15	0,07	0,010204082	
Parking						
• **Present *with* possibility to load battery** • **present *without* possibility to load battery** • **Parking: absent**	0,58 -0,33 -0,25	0,09 0,08	0,46 -0,16 -0,3	0,09 0,08	0,888888889 2,2578125	
Financial intervention by employer						
• **Present** • **Absent**	0,7 -0,7	0,08	0,42 -0,42	0,08	6,125	p<0,05
No-choice parameter	-0,82	0,05	-0,48	0,05	23,12	p<0,05

4.3.4 Location

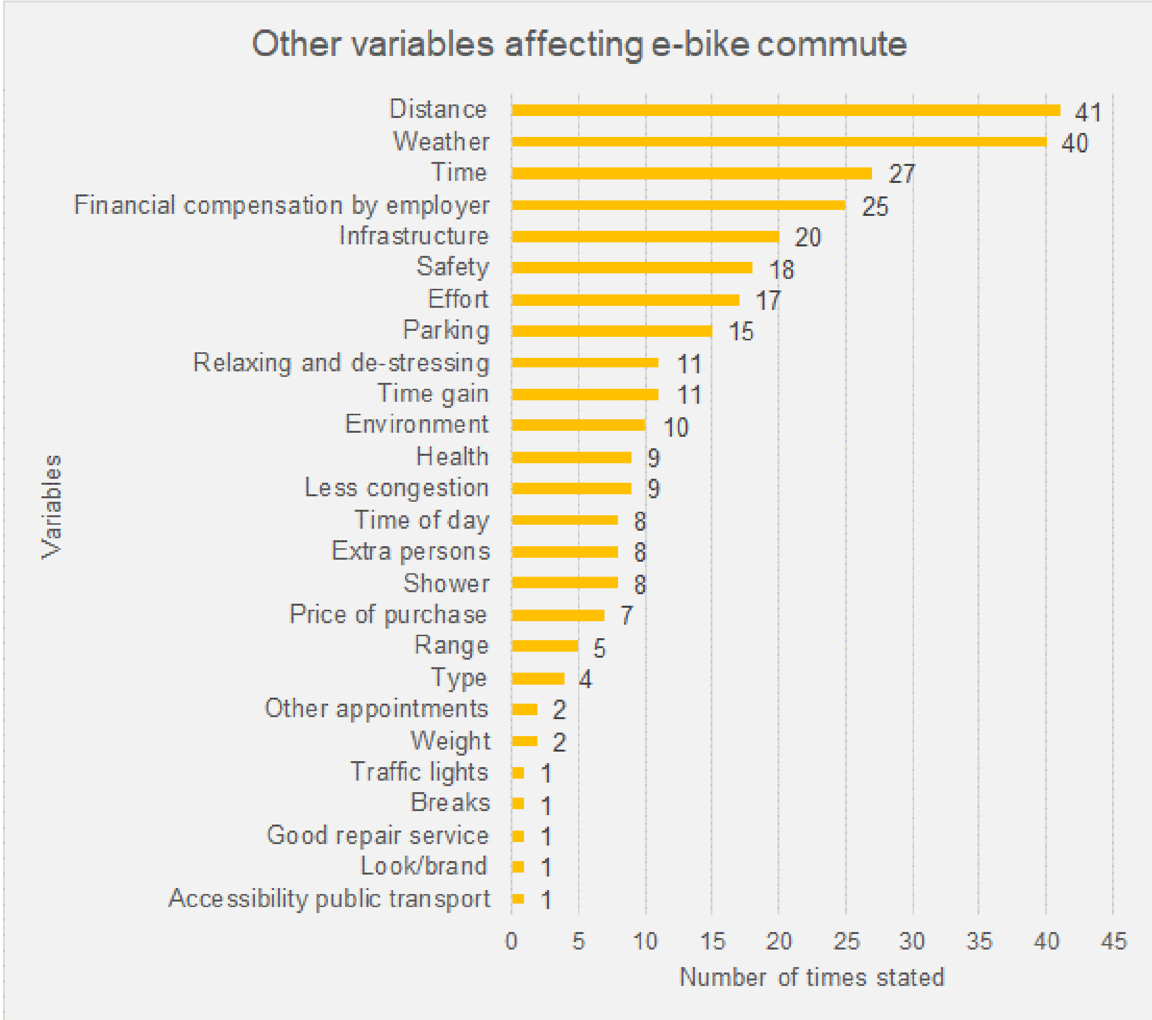
The last analysis, we did was based on the location of home and work of the respondents. This analysis had multiple difficulties since it is not entirely clear what is an urban region and what is a rural region based on postal code. When we try to do this, we see that the majority of the respondents lives or works in an urban region (86,1%) and a minority of the respondents (13,9%) lives and works in rural regions. This low number makes it impossible to guarantee significant responses for the 'rural' respondents. Therefore, we could not determine if significant differences exist in the responses of respondents commuting in urban regions and respondents commuting in rural regions.

4.4 Stated importance of variables

To control our respondents, we asked some control questions, as stated before. Yet we can use these questions further, since they were related to the variables used in the CBC. Table 11 shows these results for the different variables. Beside the factors that we investigated in this analysis; we asked the respondents what other aspects affect e-cycling to work. Graph 8 shows the different elements that the respondents mentioned.

Table 11: Stated importance of variables

Variable	**Has *an* effect**
Time	81,9%
Trajectory	74,3%
Weather	63,2%
Type	38,9%
Shower	33,3%
Parking	62,5%
Financial intervention by employer	62,5%



Graph 8: Other variables effecting e-cycling in commute

5 DISCUSSION

The results of our analysis validate our hypotheses regarding the sign of the part-worths. We see (Table 5) that all variables are significant, this implies that every variable(-level) has an effect when e-cycling to work. Some have a positive effect on the likelihood of e-cycling to work like a small amount of time, good weather, good cycling infrastructure, riding a regular e-bike, safe parking and shower present at workplace and financial support by employer present. The opposite of those levels all has a negative effect on this likelihood, as we hypothesised. The variables that have the largest effects are similar to those we hypothesised[2]. Weather (34,7%) has the largest effect in a choice. The effect of trip time (15,5%), type of e-bike (15,0%), financial intervention by employer (14,4%) and parking (10,4%) is more limited. The variables trajectory (8,9%) and shower (1,2%) have a small, but significant, effect on the likelihood of e-cycling to work.

The part-worths of the different variable-levels allow us to calculate the likelihood of the profile with the most positive attribute levels. This profile consists of the following levels: a trip time around 15 minutes, trajectory mostly on bike paths, weather is good, on a normal e-bike, shower and secured parking is present at workplace and there is financial stimulation by employer. A profile with these attribute levels has a likelihood of 94,5%[3] of being preferred. The profile that will have the smallest likelihood is the following: A commute trip that takes around 30 minutes, mostly along car roads, with bad weather, on a speedelec; at the workplace there is no shower or secured parking present and the employer offers no additional support. A profile with these attribute levels has a likelihood of 12,7%[4]. The profile that contains the none-of-these option has a 18,8%[5] chance of being taken in the full sample.

The goodness-of-fit tests of our model is relatively well (Table 7). Our model predicts 59,9% of the answers correct. The R^2-values of our model are rather low (Cox & Snell R^2 = 0,133 and Nagelkerke R^2 = 0,184). When analyzing these numbers, we need to keep in mind the different individual preferences of our 144 respondents. This makes it hard to create a model with better R^2-values. The Hosmer-Lemeshow test is significant. This implies that there is a large difference between the values that our model predicts and the observations. Yet, since we have a rather large dataset, the Hosmer-Lemeshow test might be overestimating the differences between our model and the observations, because similar to our low R^2-values, the individual preferences of the respondents are aggregated here.

[2] We hypothesized that the variables weather and trajectory have the largest effect on e-cycling to work.
[3] $\ln\left(\frac{p}{1-p}\right) = y$ = -0,649+0,375+0,280+0,528+0,587+0,143+0,802+0,557+0,817
[4] $\ln\left(\frac{p}{1-p}\right) = y$ = -0,649+0-0,280-0,528-0,587-0,143+0-0,557+0,817
[5] $\ln\left(\frac{p}{1-p}\right) = y$ = -0,649-0,817

5.1 Weather

When we look at the effect of the largest factor on e-bikes in commute, we see this are the weather conditions. Respondents focused strongly on the presence of this factor. We see that good weather (dry and not windy) positively effects e-cycling to work and when the weather is harsher (rain and windy), we see that this implies a lower likelihood. This suggest that the findings of Flynn *et al.* (2012) for regular bicycles also apply to e-bikes. Weather is the most determining factors when cycling to work. This finding is in line with the academic literature on the effect of weather on (e-)cycling in commute (Campbell *et al.*, 2016; Flynn *et al.*, 2012; Lopez *et al.*, 2017; Nematchoua *et al.*, 2020; Sears *et al.*, 2013; van den Bergh *et al.*, 2018). Lopez *et al.* (2017) suggest that weather conditions have more influence on recreational trips than on commuting trips. Here we focused only on commute trips, but we see also in commute a very large effect of the weather conditions.

The large effect of weather on the likelihood of using an e-bike to work implies that the weather conditions are the determining factor when e-cycling to work (i.e. in our context, in reality, other factors might influence this choice even more). This large effect of weather means that e-cycling in commute a daily decision is, which is hard to affect by other elements like investments or financial stimulation. Yet, when we look at the weather conditions in Flanders, we see that it rains only a limited amount of time, it only rains 7% of the time in Flanders (Fietsberaad Vlaanderen, 2018). The large impact of weather suggests further that for many, riding an e-bike to work in bad weather conditions is no option.

5.2 Trip time

The factor with the second largest effect on e-cycling to work is 'trip time' (15,5%). This is not only visible in the results of the CBC, but also in the results of the stated importance of the factors. Trip time is very often (81,9%) stated as important by the respondents in the control questions. On the question, "what factors would affect e-cycling to work?", we see that trip time (27 responses) and trip distance (41 responses) are one of the main concerns for people (as discussed before time and distance are very much correlated in mobility). These results show multiple times that the time of commute is very important. We see that the longer the travel time a trip, the less attractive it becomes. This is similar to the results of Te Morsche *et al.* (2019), van den Bergh *et al.* (2018) and Nematchoua *et al.* (2020).

The positive effect of small amount of time, around 15 minutes, show that e-bike is a mode that especially has potential for people who live in short range distance (i.e. small amount of time) of their work. The rather large focus on time implies that people are trying to optimize their commute trip time. This is a real potential for e-bike in commute. If e-bikes succeed in being faster than other transport modes on these short trips, this might increase the modal shift to e-bikes. When people live further from work this potential decrease, since other modes will be faster. Yet we see that trip times between 15 and 30 minutes, still have a rather large positive effect compared to trip times of 30 minutes.

5.3 Type

The factor with the third largest effect in our CBC-analysis is the type of e-bike. In the stated preference, we do not see this result (low percentage in Table 11 and only 4 times mentioned in Graph 8). Many people feel that the type of e-bike is no determining factor in their commute.

We see that there is clear difference between a regular e-bike and a speedelec. Regular e-bikes have a positive likelihood of e-cycling to work, while for speedelecs this decreases this chance. The explanation of this might be linked with the unsafe image of speedelecs. The willingness of attaining a speedelec is very limited we see (5,7% of the 144 respondents). For regular e-bikes, we see larger numbers. This confirms that a speedelec and a regular e-bike are two separate type of bicycles and should be regarded this way. The differences in price and speed make that they have different characteristics. Policy actions that want to improve the modal share of these two modes need to be chosen carefully.

5.4 Financial intervention by employer

The factor 'financial intervention by employer' has a similar importance (14,4%) as the factor type of e-bike. The importance of this factor is confirmed in the results of the stated importance. We see that the presence of financial support, positively affect e-cycling to work. This relatively large effect of 'financial support by employer' is similar to the findings in the literature. Nematchoua *et al.* (2020) found similar to our findings that financial support has a rather large effect on e-cycling. Wardman *et al.* (2007) also found a clear positive effect between additional financial support and more cycling to work.

Our result suggests that there is a clear role for the employer and indirect for policy makers in e-cycling to work. As discussed before, the existing financial support, mileage allowance and e-bike leasing, already helps convincing people towards (e-)bikes (Vanoutrive *et al.*, 2009). An additional financial stimulation can even more increase e-cycling to work.

5.5 Parking

At the working place, not only the financial support is important. As our results show, a parking at the workplace is similarly important. If no secured parking is present, this decreases the likelihood of e-cycling to work. This is in line with the findings in the academic literature (Abraham *et al.*, 2002; Fietsberaad Vlaanderen, 2013; Heinen *et al.*, 2013; Heinen & Buehler, 2019; Stewart *et al.*, 2015; Vanoutrive *et al.*, 2009). The presence of a secured parking at the workplace enhances not only the likelihood of cycling to work, but our results suggest that this is certainly also the case for e-cycling.

When we look what sort of parking has the lowest likelihood, we see that the difference between a secured parking without possibility to charge battery of e-bike and no parking is limited (very similar parth-worths).

This makes us suggest that not only the presence of a secured parking is important for e-bikes, but also the presence of a possibility to charge the battery of the e-bike. We can link the latter with the range anxiety that some people have over e-bikes. They fear that the battery will run out of energy and they will have to e-cycle without the support of the battery. Having the possibility to charge the e-bike battery at the working place seems to solve this problem for them. This is somewhat surprising, as for most e-bikes it is possible to remove the battery (a demountable battery) and charge it somewhere else (e.g. inside the workplace). Our result shows that many prefer to leave the battery on the bike and in the secured parking.

5.6 Infrastructure

Furthermore, we see a limited impact of infrastructure in the preference structure in our analysis. Adapted infrastructure to cycling positively affects e-cycling to work. When this is not available, the likelihood of using an e-bike to works decreases. This is line with academic literature on this topic (Buehler & Pucher, 2012; Howard & Burns, 2001; Mertens *et al.*, 2016; Mueller *et al.*, 2018; Nematchoua *et al.*, 2020; Stewart *et al.*, 2015; Rotthier *et al.*, 2017; Vanoutrive *et al.*, 2009; Wooliscroft & Ganglmair-Wooliscroft, 2014).

Wooliscroft and Ganglmair-Wooliscroft (2014) found similarly to our results that the effect of infrastructure on e-cycling to work is not the most important attribute. They state the following over this: “It is likely that the utility of cycle lanes recognizes the fact that even when significant cycle lanes are provided cyclists will still spend part of their trip on shared roads with car drivers.” (Wooliscroft & Ganglmair-Wooliscroft, 2014, p. 18). This is an important statement. Now, it is seldom the case that an e-cyclist only uses cycling lanes. Our variable level stated similarly ‘*mostly* cycling paths’ to offer a realistic profile. Yet our results suggest that the more cycling path is available to a commuter, the higher the likelihood a respondent will use those cycling paths. This confirms the incentive of the Flemish government to invest in cycling paths. Mertens *et al.* (2016) state (in a different context) that the most important variable is the type of cycling path.

5.7 Shower

Shower is the factor with the lowest relative importance. This finding is supported with the stated importance of this factor. Respondents see this as a variable that is very limited important. We see that the presence of a shower has a small but positive effect on the likelihood.

The finding of Abraham *et al.* (2002), Heinen *et al.* (2013) and Stewart *et al.* (2015) show that the presence of a shower is rather important for regular cyclists. The lower importance, we find here, might be related to the lower physical effort needed when riding an e-bike. This lower effort could create in a lower need for the presence of a shower.

5.8 Other factors affecting e-bike use

When we look at what other variables effect e-cycling in commute (Graph 6), we see that beside the seven used aspects in the profiles, some other aspects do play a role. The most stated ones are distance, safety, effort, relaxing and de-stressing, time gain, environment, health, less congestion, time of day and transporting extra people.

Although distance and time are closely related factors, many respondents still feel that there is a difference between those two aspects. Furthermore, the safety aspect of e-bikes is a factor that plays a role for some respondents. The same for the factor ‘environment’. For a small group of respondents, this durable aspect affects their commute mode choice. Other factors worth mentioning are effort and closely related health benefit. Some respondents see e-bikes as a good way to work out to work in a comfortable way, i.e. the factor relaxing and de-stressing. For some respondents the factor time gain and less congestion is important. We argued before that especially on short distances in urban environments, regular e-bikes can compete with cars. For speedelecs, this range is even larger (Rotthier *et al.*, 2017). The factor ‘time of day’ is presumably related to people working at irregular hours, very early or very late. For trips at those hours e-bikes are less appealing. We did not discuss this disadvantage before. Another disadvantage that we did discus before is the transport of other people before or after work. For children or smaller goods, cargo e-bikes can offer a solution. For other purposes, e-bikes do not offer a way out.

5.9 Effect of user-characteristics

5.9.1 Gender

When we look at the results of the role of user-characteristics, we see several tendencies. We see multiple differences between male and female respondents. We see that the attribute levels: time around 15 minutes and type are significantly different. Just as the none-of-these alternative. For the difference in time, we see that female respondents evaluate a shorter trip higher than male respondents do. When we compare the trip time of male and female respondents (Graph 7), we see that female respondents live slightly closer to work than male respondents. The reason for this is unclear. The significance of type is similarly unclear. We see that the difference between a regular e-bike and a speedelec is not as large with male respondents than for female respondents. Female respondents evaluate regular e-bike highly positive and speedpedelecs highly negative. For male respondents this difference is more moderate, although they also evaluate regular e-bike positive and speedpedelecs negative. Our results are not similarly to the findings of Nematchoua *et al.* (2020). They found no significant differences between male and female users based on speed.

The coefficients of the intercept and the none of these alternative makes us conclude that the likelihood of e-cycling increases when female and decreases when male. The none-of-these alternative is slightly chosen more in our study by male than by female respondents[6]. Cherry and Cervero (2007) found similar results to our findings; Wooliscroft and Ganglmair-Wooliscroft (2014) found no effect of gender. Campbell *et al.* (2016) found that the likelihood of e-cycling decreases when female. There might be an effect here of the context of this study, shared e-bikes in Chinese cities.

5.9.2 E-bike ownership

When looking at our group of e-bike owners (54 respondents), we see (Table 4) that they are older and higher educated than non e-bikers, this is in line with results in the academic literature (Cherry and Cervero, 2007; Johnson & Rose, 2013; MacArthur *et al.*, 2014; Wolf & Seebauer, 2014). Two third of the e-bike owners are female. This result (although a smaller sample size) is very similar with other findings of e-bike gender in a Flemish context (58,7% female and 41,3% male) (Gemeente- en stadsmonitor Vlaanderen, 2017; IMOB 2017). Furthermore, we see that e-bike owners, on average, live slightly further from home than non e-bike owners (Graph 7). This supports our statement that e-bikes have a large potential in commute for people that do not want to ride a regular bicycle to work.

The only variable that is significantly different between the e-bike owners and the non e-bike owners is the type of e-bike. For both groups a regular e-bike has a positive likelihood and speedelecs have a negative likelihood. Yet for e-bike owners this is more pronounced than for non e-bike owners. We can argue that the difference between the two types is less determining for the non e-bike owners than the e-bike owners. This can be related to the type of e-bike they possess themselves. We did not ask the e-bike owners what type of e-bike they possessed, yet we presume that the majority of the e-bike owners owns a regular e-bike.

Zijlstra (2016) suggest similarly that non e-bike owners are less tied to one type but find different types interesting, where e-bike owners will choose more for their own type of pedelec. In addition, we see a difference in the WTP for an e-bike between all respondents and e-bike owners. Those who already have an e-bike show a higher WTP. This is in line with the findings of Fyhri *et al.* (2017) and Zijlstra (2016) that suggest that experience with an e-bike leads to higher WTP.

5.9.3 Age

When we look at the significant differences between our young and old group. We see that similarly to the difference based on gender, that the part worth of the levels time around 15 minutes and the none-of-these alternative are significant. Additionally, the part worth of the factors weather and financial support by employer is also significant different here. The younger age group evaluates a shorter time more positive than the older age group does. Similarly, for good and bad weather, the younger respondents evaluate the weather respectively more positive and negative than the older age group. The same way of thinking applies to the

[6] $p = \frac{1}{1+e^{-y}}$ with y = -0,96 + 0,77 (for male respondents) and y = -0,74 +0,57 (for female respondents)

variable ‘financial support by employer’. We can conclude that the preferences of both groups are similar, but in younger age group this is more pronounced than in the older age group.

The none-of-these alternative has a higher likelihood in the young age group[7]. This makes us conclude that choosing to e-cycle is more likely when older than younger. Campbell *et al.* (2016) and Cherry and Cervero (2007) found that the older the respondent the higher the likelihood a person will e-cycle.

5.10 Policy implications

Our findings suggest some policy implications. Those are rather similar to the suggested policy actions to improve regular cycling, yet there are some minor differences. A first element here are the weather conditions. This is the largest factor that affects e-cycling to work. This is one of the factors that are difficult to influence by policy actions (Cherry & Cervero, 2007.) Other factors that cannot be affected immediately are daily circumstances (e.g. picking up goods or children) and attitudinal factors (e.g. attitude towards cycling, finding cycling pleasant, etc.). Together with the weather conditions, those two have an effect on the mode choice in commute (Heinen, 2010; Heinen *et al.*, 2013; Van Acker *et al.*, 2020). Although the weather is hard to influence, we can approach it in a different way. There exists a famous Danish saying that says: “There is no such thing as bad weather, only bad clothing”. This quote applies as well for e-cycling. There are also some small acts policy makers can do to improve (e-)cycling conditions when the weather is bad, e.g. making sure cycling paths remain snow free and showing cyclists that protective clothing exists. All of this keeping in mind that it only rains 7% of the time in Flanders (Fietsberaad Vlaanderen, 2018).

Beside weather and attitudinal factors, there are multiple factors that policy makers do have a direct effect on. Improving those factors that are preferred might improve the modal share of (e-)bikes in commute, but also in other trip purposes. A first major element here is the cycling infrastructure. Pucher and Buehler (2008) suggest regarding this topic that “The key to achieving high levels of cycling appears to be the provision of separate cycling facilities along heavily travelled roads and at intersections, combined with traffic calming of most residential neighbourhoods.” (Pucher & Buehler, 2008, p. 495). The Flemish government aims to accomplish this already. Yet our results show that this will affect e-cyclists as well. We see as well that only investing in cycling infrastructure will only create a small improvement of e-cycling to work. Investments at facilities at the working place, like secured parking and to a lesser extent the possibility to use a shower, are similarly important to realize the modal shift towards e-bikes in commute. Furthermore, we see that the presence of ‘financial stimulation by employer’ increases the likelihood of e-cycling to work. Financial stimulation is therefore an extra factor and investment that can help accomplishing this modal shift.

Making sure these actions happen, will require a cooperation between several departments of the Flemish Government. The main one is the Department of Mobility and Public Works. This department is responsible

[7] $p = \frac{1}{1+e^{-y}}$ with y = -0,86 + 0,82 (for the young age group) and y = -0,79 +0,48 (for the young age group)

for sufficient and high-quality cycling lanes and promoting e-cycling in the population. At the same time, there is a role for the Department of Education and Training, to educate the future cyclists to make sure cycling remains safe and pleasant. The Department of Environment has a specific task here, to create a spatial planning that suits the needs of people while keeping the distances to reach all essential functions in (e-)bike range of their home. Furthermore, to help employers give a financial stimulation to employees who (e-)cycle to work, the Department of Finance at Flemish and federal levels might help. As we discussed before, the Department of Public Health, can benefit of the advantages of e-cycling. The promotion of active transport is therefore something wherein this department can help.

In addition, policy decisions should avoid aiming only at one type of e-bikes, often speedpedelec users. For this mode the cycling highways are perfectly suited and the tax-profit when leasing of e-bikes, is extra profitable for the more expensive speedelecs. Our findings suggest that regular e-bikes are more wanted then speedelecs. Investments in this mode will therefore only affect a small group of users. There is a larger potential in the regular e-bikes, as the sales numbers show. The e-bike should therefore become a transport mode that is accessible for all.

The latter is especially important, when we look at the recent tendency that people start to use more private transport. Due to the COVID-19 pandemic, the use of public transport is reduced strongly (De Vos, 2020). As we have seen before the modal shift towards e-bikes comes largely from public transport. This tendency is therefore an important challenge for e-bikes to attract more people to this mode. The cost of an (e-)bike is far lower than the cost of other private transport modes, this makes (e-)cycling more social transport mode. If policy achieves at enlarging the modal shift from public transport to e-bikes, this might enforce the position of an e-bike as a social durable transport mode that offers an alternative for other modes, e.g. in commute.

Beside all of this, our results make clear as well that e-bike are no one-fit solution in accomplishing a sustainable way for commute. For people that live in long-range distance from their workplace, other solutions are necessary (teleworking, high functioning public transport, and others).

5.11 Limitations

As in any, our investigation also showed some flaws. We can distinguish four categories of limitations or improvements we could do in further analysis. The first category is related how we approached the respondents in the questionnaire. We could show them more explicitly what we mean with each attribute level. Especially for the levels were this could be unclear. Photos of the different types of trajectory, weather, parking facility and e-bike type could help the respondents in making realistic choices. Additionally, we could use more location specific attributes to create profiles that are more realistic.

To know what other factors might affect the e-bike use of the respondents, it could have been better to give the respondents already some pre-made options and an option of other. This would avoid that some respondents ignored this question and would lead to better results.

Furthermore, we could do in-depth interviews with e-bike commuters and potential e-bike commuters asking questions on when they use their e-bike, what mode did e-bikes replace, what they feel advantages and disadvantages of e-bikes are and what their expectations of e-bike use is. Having more in-depth info, could allow us to have a better understanding of the preference structure of e-bikes in commute.

The second category of limitations is closely related to the latter, namely the factors we used in the stated preference analysis. Having a better understanding of the factors that the current e-cyclists feel that are important can affect our choices for the factors we use. The whole analysis evidently depends on the factors we choose to investigate here. This affects our results and what conclusions as well we can draw from them.

The third category is related to the stated preference analysis itself. Instead of using a combination of effect coding and dummy coding, we could use only one type of coding (here dummy coding) to have a more coherent image of the results. Furthermore, using a stated preference analysis made it not possible to investigate here if there exists a difference between people living in urban or in rural regions. More respondents and a better spatial distribution of the respondents would make it possible to do this analysis and have significant results.

The last category are possible further analyses. We could investigate employees of several companies by asking what is available at their working place (i.e. shower, sort of parking and financial support), see what the modal share for different modes at different companies is and check if the presence of a secured parking, shower or financial support relates with more (e-)bike commute. Furthermore, instead of asking what e-bike profile they like most, we could ask the same question between different transport modes, similar to van den Bergh *et al.* (2018). This would allow us to know how the preference structure of an e-bike compares to the preference structure of a similar mode (regular bicycle, moped or public transport). Having this information, can help policy makers to know what the needed contextual factor for e-bikes and other modes are (Cherry & Cervero, 2007; Cherry *et al.*, 2009). In further analysis, we could focus on e-bike commuters in one specific city, rather than a region (i.e. Flanders).

6 CONCLUSION

The call for a more sustainable society becomes louder and louder. One of the different solutions that will be necessary to achieve this, are sustainable transport modes. In the broad range of upcoming transport modes, one of the upcoming modes are e-bikes. This electrical type of bicycles shows to have an interesting potential, especially regarding commuting. The rising sales numbers of e-bikes in Belgium, Europe and abroad show that an increasing part of the population can use this transport mode. E.g. more than half of all sold bicycles in Belgium in 2019 were e-bikes. Furthermore, we see that a large amount of the Flemish population, in this case approximately 60%, live in e-bike range (distance around 15 km) from their work (IMOB, 2020).

The combination of those two factors, increasing sales numbers and low commute distances, together with the main advantage of an e-bike, electrical assistance when pedalling, which makes cycling easier, create a potential for e-bikes in commute. We see as well that the modal shift towards e-bikes is at this moment largely from public transport and regular cycling. To realize a substantial modal shift from private motorized transport like cars to durable transport modes, e.g. e-bikes, policy measures will be needed.

At the same time, we see that policy makers try to stimulate (e-)cycling in commute with measures as investments in bicycle infrastructure and providing financial stimulation for cycling (high mileage allowance in Belgium and tax profit when leasing e-bikes). While taking those measures, policy makers need to realise that there are multiple different elements affecting the choice when (e-)cycling to work. We investigated in this master's thesis what is the effect of those two and five other factors on the likelihood of e-cycling to work. To investigate this, we did a stated preference analysis and more specific a choice-based conjoint analysis (CBC).

The factors and factor levels used in our CBC were determined using academic literature. The investigated factors were: 'trip time', 'bike trajectory', 'weather conditions', 'type of e-bike', 'availability of a shower at workplace', 'availability of a secured parking at workplace', 'financial intervention by the employer'. The factor levels we used for each factor were respectively 15 minutes – between 15 and 30 minutes – 30 minutes for the factor trip time, mostly cycling paths – mostly along car roads for the factor bike trajectory, good – bad for the weather conditions, normal e-bike – speedelec for the factor type of e-bike, present – absent for the factor availability of a shower at the workplace, present (with possibility to load battery) – present (without possibility to load battery) – absent for the factor availability of a secured at the workplace and yes – no for the factor financial intervention by the employer.

A full fractional design of those factor levels was created with all possible profiles. This led to 288 different combinations. Showing all those options to the respondents is not preferable. Therefore, we reduced those to sixteen options in a fractional factorial design using the Fedorov algorithm. A questionnaire was created that included sixteen CBC-questions with a third none-of-these option. The questionnaire included as well multiple questions that gauged for other characteristics of the respondents. 154 respondents filled in the full survey. After data cleaning, this number was reduced to 144 respondents. Using a no-choice binomial logit model, we could estimate the values of the coefficients of the different variable levels. This allowed us as well to determine what factors have the largest impact on the likelihood of choosing an e-bike when going to work.

The results of the stated preference analysis in this master's thesis show that the weather conditions have the largest effect on the likelihood of choosing an e-bike in commute. After this factor, the factors trip time, type of e-bike and financial intervention by employer were the most important factors. The availability of parking, the trajectory and the presence of a shower at the workplace show to be the least important factors.

Furthermore, we see related to the policy actions regarding this topic that investments in infrastructure and additional financial intervention by the employer have a positive effect on the. Yet those factors are not the most important compared to others. We see that the presence of cycling infrastructure positively affects e-cycling. Further investments in this remain therefore important to realize a modal shift towards e-bikes.

Our results suggest that there is as well a role for the employer in achieving a modal shift towards e-bikes. Offering facilities like a secured parking (especially with or the possibility to charge the battery of your e-bike), financial stimulation and to a lesser extent showering facilities all increase the likelihood of e-cycling in commute. The possibility to charge the e-bike shows to very important when e-cycling to work. The low impact of the presence of a shower, can be related to the lower physical effort when riding an e-bike, mainly thanks to the electrical assistance.

To achieve a modal shift towards e-bikes, it can also be interesting to focus on specific groups. We applied a CBC-analysis with a Wald Chi square statistic to see if there exist differences based on differences in respondent characteristics. The characteristics we investigated here were gender (male and female respondents), e-bike ownership (e-bike owners and non e-bike owners), age (young and older respondents, respectively to average age of all respondents) and location (urban or rural living context).

We found that females show a higher likelihood of e-cycling to work, since they choose the none-of-these option less frequently than male respondents. Female respondents also showed a higher dependence on the type of e-bike, they prefer a regular e-bike more than male respondents, yet both show to choose a regular e-bike over a speedelec.

The group of e-bike owners differed only from the non e-bike owners respondents based on type of e-bike. E-bike owners show a larger reluctance towards speedelecs than non e-bike owners do. Similarly, they show a higher preference towards a regular e-bike than non e-bike owners do.

Based on age, we see that older respondents show a higher likelihood of e-cycling than younger respondents, since they choose the none-of-these option less frequently. A short trip time, good weather conditions and a present financial intervention by employer are preferred more by younger respondents than older respondents. Yet we see that the sign is similar, only the magnitude of the coefficients differs between the two groups of respondents. Our results made it not possible to determine if there exist differences between people living in urban regions and people living in rural regions.

When we look at what other factors people find important in the context of e-cycling to work. We see that closely related to the factor trip time; trip distance is seen as important. Furthermore, the factors safety, physical effort and relaxing/de-stressing show to be evaluated high by the respondents.

Beside the direct policy actions or actions by the employer, our study shows factors as well that are more difficult to influence by policymakers. Bad weather, the type of e-bike a person can use and the trip time are examples of this. Together with investments in safe and high-quality cycling infrastructure other policy implications might be needed. Showing people alternative of protective clothing when cycling in bad weather conditions, approaching normal e-bikes and speedelecs as two separate transport modes and spatial planning strategies that reduces the number of people that live in far range distances from their work. E-bikes can also be an alternative for other private transport modes since it is more social than cars and public transport use might be reduced due to the COVID-19 pandemic.

Our study showed some limitations. A first one was the limited spatial distribution of the respondents which made it impossible to distinguish enough respondents living in rural regions. Other limitations are the way we approached the respondents, showing pictures of what is meant with each variable level in the CBC would have been helpful.

The determination of the factors used in the CBC could also be more funded, using e.g. in-depth interviews with e-bike commuters. This would allow us to choose maybe more relevant attribute levels. Furthermore, a narrower region of investigation would lead to more contextual factors. We could ask respondents what is available now at the workplace and see how this affect e-bike ridership to work. In further analysis we could do as well a more broad CBC. Instead of focussing only on e-bikes, we could investigate those factors in combination with other related transport modes (such as regular bicycles, mopeds and public transport).

We can conclude that e-bikes show a large potential in commute. Multiple factors influence directly and indirectly to use this transport mode. Policy actions to promote e-cycling and attitudinal changes of people can help fulfil e-bike their potential.

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8 APPENDIXES

8.1 Appendix A - Experimental design in RStudio

Coding CBC (experimental design and randomization over two sets)

```
#call in library

 library(AlgDesign)

# create full factorial design with all different options

 fullfd <- gen.factorial(c(3,2,2,2,2,3,2),varNames=c('TIME','TRAJECT',

'WEATHER', 'TYPE', 'SHOWER', 'PARKING', 'FINANCIAL'), factors='all')

#setting random seed

 set.seed(99849843)

#creating factorial design

 fact_des <- optFederov(~., data= fullfd, nTrials= 16, approximate = TRUE)

#accounting design to one alternative

 alt1 <- fact_des$design

 alt1

#setting same possibilities to other alternative

 alt2 <- alt1

#create new column in 2 alternatives

 alt1 <- transform(alt1, r1 = runif(16))

 alt2 <- transform(alt2, r2 = runif(16))

#sort alternatives on random value r
```

```
alt1_sort <- alt1[order(alt1$r1),]

alt2_sort <- alt2[order(alt2$r2),]

#print 2 different variable options

alt1_sort

alt2_sort

as.numeric(rownames(alt1_sort))

as.numeric(rownames(alt2_sort))
```

The function ‘optFederov’ has three arguments: ‘~.’, ‘ffd’, and ‘16’. The first argument, ‘~.’, implies that all data variables are used linearly and their names are used in the model. The second argument, ‘ffd’, indicates the name of the data that contains the full candidate list. This is the same as the name of the object containing the full factorial design created before. The last argument, ‘16’, indicates the number of rows (alternatives or profiles) in the fractional factorial design.

8.2 Appendix B - Full survey

Below, are screenshots of the full survey presented as it was shown to the respondents. The answers to the survey from all respondents can be found in the digital attachments.

LimeSurvey

Elektrische fietsen in het woon-werkverkeer

Beste deelnemer,
Beste deelneemster,

Hartelijk dank voor uw interesse aan het onderzoek naar de voorkeuren van werknemers om met een elektrische fiets naar het werk te rijden.
Om deel te nemen is het niet noodzakelijk dat u nu reeds met een elektrische fiets naar uw werk rijdt.
Uw antwoorden zijn persoonlijk en vertrouwelijk.
Deze vragenlijst invullen vraagt **ongeveer 10 minuten**.

Alvast bedankt

Corneel Casier, student 2e Master Geografie
Prof. Dr. Frank Witlox, promotor
Universiteit Gent, vakgroep Geografie

LimeSurvey

Hervat later

er

25%

Deze enquête is nu niet actief. Uw antwoorden kunnen niet worden opgeslagen.

*Naar welke van deze alternatieven gaat uw voorkeur?

Kies maximaal één antwoord

☐ Tijd traject bedraagt ongeveer	**30 minuten**
Het traject van uw fietsroute gaat	**veelal via autoweg**
Weersomstandigheden zijn	**ongunstig: nat en veel wind**
Type elektrische fiets	**Speedelec (< 45 km/h)**
Douche op uw werkplek	**Afwezig**
Beveiligde parking op uw werkplek	**Aanwezig, zonder oplaadpunt**
Financiële tussenkomst door werkgever	**Ja**

☐ Tijd traject bedraagt ongeveer	**30 minuten**
Het traject van uw fietsroute gaat	**veelal via autoweg**
Weersomstandigheden zijn	**ongunstig: nat en veel wind**
Type elektrische fiets	**Speedelec (< 45 km/h)**
Douche op uw werkplek	**Aanwezig**
Beveiligde parking op uw werkplek	**Aanwezig, met oplaadpunt**
Financiële tussenkomst door werkgever	**Ja**

☐ Geen van beide opties, liever met een ander vervoermiddel, zoals auto, bus, ...

Douche op uw werkplek	**Afwezig**
Beveiligde parking op uw werkplek	**Aanwezig, zonder oplaadpunt**
Financiële tussenkomst door werkgever	**Neen**

☐ Tijd traject bedraagt ongeveer	**tussen 15 en 30 minuten**
Het traject van uw fietsroute gaat	**veelal via autoweg**
Weersomstandigheden zijn	**ongunstig: nat en veel wind**
Type elektrische fiets	**Speedelec (< 45 km/h)**
Douche op uw werkplek	**Aanwezig**
Beveiligde parking op uw werkplek	**Aanwezig, zonder oplaadpunt**
Financiële tussenkomst door werkgever	**Neen**

☐ Geen van beide opties, liever met een ander vervoermiddel, zoals auto, bus, ...

*Naar welke van deze alternatieven gaat uw voorkeur?

Kies maximaal één antwoord

☐ Tijd traject bedraagt ongeveer	**tussen 15 en 30 minuten**
Het traject van uw fietsroute gaat	**veelal via autoweg**
Weersomstandigheden zijn	**ongunstig: nat en veel wind**
Type elektrische fiets	**Speedelec (< 45 km/h)**
Douche op uw werkplek	**Aanwezig**
Beveiligde parking op uw werkplek	**Afwezig**
Financiële tussenkomst door werkgever	**Ja**

☐ Tijd traject bedraagt ongeveer	**30 minuten**
Het traject van uw fietsroute gaat	**veelal via autoweg**
Weersomstandigheden zijn	**gunstig: droog en weinig tot geen wind**
Type elektrische fiets	**Normale elektrische fiets (< 25 km/h)**
Douche op uw werkplek	**Aanwezig**
Beveiligde parking op uw werkplek	**Afwezig**
Financiële tussenkomst door werkgever	**Neen**

☐ Geen van beide opties, liever met een ander vervoermiddel, zoals auto, bus, ...

*Naar welke van deze alternatieven gaat uw voorkeur?

Kies maximaal één antwoord

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Douche op uw werkplek	**Aanwezig**
Beveiligde parking op uw werkplek	**Afwezig**
Financiële tussenkomst door werkgever	**Neen**

☐ Tijd traject bedraagt ongeveer	**tussen 15 en 30 minuten**
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Type elektrische fiets	**Normale elektrische fiets (< 25 km/h)**
Douche op uw werkplek	**Aanwezig**
Beveiligde parking op uw werkplek	**Aanwezig, zonder oplaadpunt**
Financiële tussenkomst door werkgever	**Neen**

☐ Geen van beide opties, liever met een ander vervoermiddel, zoals auto, bus, ...

*Naar welke van deze alternatieven gaat uw voorkeur?

Kies maximaal één antwoord

☐ Tijd traject bedraagt ongeveer	**30 minuten**
Het traject van uw fietsroute gaat	**veelal via autoweg**
Weersomstandigheden zijn	**ongunstig: nat en veel wind**
Type elektrische fiets	**Speedelec (< 45 km/h)**
Douche op uw werkplek	**Aanwezig**
Beveiligde parking op uw werkplek	**Aanwezig, met oplaadpunt**
Financiële tussenkomst door werkgever	**Ja**

☐ Tijd traject bedraagt ongeveer	**tussen 15 en 30 minuten**
Het traject van uw fietsroute gaat	**veelal via fietspaden**
Weersomstandigheden zijn	**ongunstig: nat en veel wind**
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Beveiligde parking op uw werkplek	**Aanwezig, met oplaadpunt**
Financiële tussenkomst door werkgever	**Ja**

☐ Geen van beide opties, liever met een ander vervoermiddel, zoals auto, bus, ...

*Naar welke van deze alternatieven gaat uw voorkeur?

Kies maximaal één antwoord

☐ Tijd traject bedraagt ongeveer	**30 minuten**
Het traject van uw fietsroute gaat	**veelal via fietspaden**
Weersomstandigheden zijn	**ongunstig: nat en veel wind**
Type elektrische fiets	**Normale elektrische fiets (< 25 km/h)**
Douche op uw werkplek	**Aanwezig**
Beveiligde parking op uw werkplek	**Aanwezig, zonder oplaadpunt**
Financiële tussenkomst door werkgever	**Neen**

☐ Tijd traject bedraagt ongeveer	**30 minuten**
Het traject van uw fietsroute gaat	**veelal via fietspaden**
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Financiële tussenkomst door werkgever	**Ja**

☐ Geen van beide opties, liever met een ander vervoermiddel, zoals auto, bus, ...

*Naar welke van deze alternatieven gaat uw voorkeur?

Kies maximaal één antwoord

☐ Tijd traject bedraagt ongeveer	**15 minuten**
Het traject van uw fietsroute gaat	**veelal via autoweg**
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Beveiligde parking op uw werkplek	**Afwezig**
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Douche op uw werkplek	**Afwezig**
Beveiligde parking op uw werkplek	**Aanwezig, zonder oplaadpunt**
Financiële tussenkomst door werkgever	**Ja**

☐ Geen van beide opties, liever met een ander vervoermiddel, zoals auto, bus, ...

Vorige

Volgende

LimeSurvey

Hervat later

37%

Deze enquête is nu niet actief. Uw antwoorden kunnen niet worden opgeslagen.

Kies maximaal één antwoord

☐ Tijd traject bedraagt ongeveer	**30 minuten**
Het traject van uw fietsroute gaat	**veelal via fietspaden**
Weersomstandigheden zijn	**gunstig: droog en weinig tot geen wind**
Type elektrische fiets	**Speedelec (< 45 km/h)**
Douche op uw werkplek	**Afwezig**
Beveiligde parking op uw werkplek	**Aanwezig, met oplaadpunt**
Financiële tussenkomst door werkgever	**Ja**

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Het traject van uw fietsroute gaat	**veelal via autoweg**
Weersomstandigheden zijn	**gunstig: droog en weinig tot geen wind**
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Douche op uw werkplek	**Aanwezig**
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Kies maximaal één antwoord

☐ Tijd traject bedraagt ongeveer	**tussen 15 en 30 minuten**
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Weersomstandigheden zijn	**ongunstig: nat en veel wind**
Type elektrische fiets	**Normale elektrische fiets (< 25 km/h)**
Douche op uw werkplek	**Aanwezig**
Beveiligde parking op uw werkplek	**Aanwezig, zonder oplaadpunt**
Financiële tussenkomst door werkgever	**Neen**

☐ Tijd traject bedraagt ongeveer	**tussen 15 en 30 minuten**
Het traject van uw fietsroute gaat	**veelal via autoweg**
Weersomstandigheden zijn	**gunstig: droog en weinig tot geen wind**
Type elektrische fiets	**Normale elektrische fiets (< 25 km/h)**
Douche op uw werkplek	**Afwezig**
Beveiligde parking op uw werkplek	**Aanwezig, zonder oplaadpunt**
Financiële tussenkomst door werkgever	**Ja**

☐ Geen van beide opties, liever met een ander vervoermiddel, zoals auto, bus, ...

*Naar welke van deze alternatieven gaat uw voorkeur?

Kies maximaal één antwoord

☐ Tijd traject bedraagt ongeveer	**15 minuten**
Het traject van uw fietsroute gaat	**veelal via fietspaden**
Weersomstandigheden zijn	**gunstig: droog en weinig tot geen wind**
Type elektrische fiets	**Speedelec (< 45 km/h)**
Douche op uw werkplek	**Afwezig**
Beveiligde parking op uw werkplek	**Aanwezig, zonder oplaadpunt**
Financiële tussenkomst door werkgever	**Ja**

☐ Tijd traject bedraagt ongeveer	**tussen 15 en 30 minuten**
Het traject van uw fietsroute gaat	**veelal via autoweg**
Weersomstandigheden zijn	**ongunstig: nat en veel wind**
Type elektrische fiets	**Speedelec (< 45 km/h)**
Douche op uw werkplek	**Aanwezig**
Beveiligde parking op uw werkplek	**Afwezig**
Financiële tussenkomst door werkgever	**Ja**

☐ Geen van beide opties, liever met een ander vervoermiddel, zoals auto, bus, ...

*Naar welke van deze alternatieven gaat uw voorkeur?

Kies maximaal één antwoord

- [ ]

Tijd traject bedraagt ongeveer	**tussen 15 en 30 minuten**
Het traject van uw fietsroute gaat	**veelal via fietspaden**
Weersomstandigheden zijn	**ongunstig: nat en veel wind**
Type elektrische fiets	**Speedelec (< 45 km/h)**
Douche op uw werkplek	**Aanwezig**
Beveiligde parking op uw werkplek	**Aanwezig, met oplaadpunt**
Financiële tussenkomst door werkgever	**Ja**

- [ ]

Tijd traject bedraagt ongeveer	**15 minuten**
Het traject van uw fietsroute gaat	**veelal via fietspaden**
Weersomstandigheden zijn	**ongunstig: nat en veel wind**
Type elektrische fiets	**Normale elektrische fiets (< 25 km/h)**
Douche op uw werkplek	**Afwezig**
Beveiligde parking op uw werkplek	**Aanwezig, zonder oplaadpunt**
Financiële tussenkomst door werkgever	**Neen**

- [ ] Geen van beide opties, liever met een ander vervoermiddel, zoals auto, bus, ...

*Naar welke van deze alternatieven gaat uw voorkeur?

Kies maximaal één antwoord

- [ ]

Tijd traject bedraagt ongeveer	**tussen 15 en 30 minuten**
Het traject van uw fietsroute gaat	**veelal via autoweg**
Weersomstandigheden zijn	**gunstig: droog en weinig tot geen wind**
Type elektrische fiets	**Normale elektrische fiets (< 25 km/h)**
Douche op uw werkplek	**Afwezig**
Beveiligde parking op uw werkplek	**Aanwezig, zonder oplaadpunt**
Financiële tussenkomst door werkgever	**Ja**

- [ ]

Tijd traject bedraagt ongeveer	**30 minuten**
Het traject van uw fietsroute gaat	**veelal via autoweg**
Weersomstandigheden zijn	**gunstig: droog en weinig tot geen wind**
Type elektrische fiets	**Speedelec (< 45 km/h)**
Douche op uw werkplek	**Aanwezig**
Beveiligde parking op uw werkplek	**Aanwezig, met oplaadpunt**
Financiële tussenkomst door werkgever	**Neen**

- [ ] Geen van beide opties, liever met een ander vervoermiddel, zoals auto, bus, ...

*Naar welke van deze alternatieven gaat uw voorkeur?

Kies maximaal één antwoord

- [ ]

Tijd traject bedraagt ongeveer	**30 minuten**
Het traject van uw fietsroute gaat	**veelal via fietspaden**
Weersomstandigheden zijn	**ongunstig: nat en veel wind**
Type elektrische fiets	**Normale elektrische fiets (< 25 km/h)**
Douche op uw werkplek	**Afwezig**
Beveiligde parking op uw werkplek	**Afwezig**
Financiële tussenkomst door werkgever	**Neen**

- [ ]

Tijd traject bedraagt ongeveer	**30 minuten**
Het traject van uw fietsroute gaat	**veelal via autoweg**
Weersomstandigheden zijn	**ongunstig: nat en veel wind**
Type elektrische fiets	**Speedelec (< 45 km/h)**
Douche op uw werkplek	**Afwezig**
Beveiligde parking op uw werkplek	**Aanwezig, zonder oplaadpunt**
Financiële tussenkomst door werkgever	**Ja**

- [ ] Geen van beide opties, liever met een ander vervoermiddel, zoals auto, bus, ...

*Naar welke van deze alternatieven gaat uw voorkeur?

Kies maximaal één antwoord

☐ Tijd traject bedraagt ongeveer	**30 minuten**
Het traject van uw fietsroute gaat	**veelal via autoweg**
Weersomstandigheden zijn	**gunstig: droog en weinig tot geen wind**
Type elektrische fiets	**Speedelec (< 45 km/h)**
Douche op uw werkplek	**Aanwezig**
Beveiligde parking op uw werkplek	**Aanwezig, met oplaadpunt**
Financiële tussenkomst door werkgever	**Neen**

☐ Tijd traject bedraagt ongeveer	**30 minuten**
Het traject van uw fietsroute gaat	**veelal via fietspaden**
Weersomstandigheden zijn	**ongunstig: nat en veel wind**
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Douche op uw werkplek	**Aanwezig**
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Financiële tussenkomst door werkgever	**Neen**

☐ Geen van beide opties, liever met een ander vervoermiddel, zoals auto, bus, ...

*Naar welke van deze alternatieven gaat uw voorkeur?

Kies maximaal één antwoord

☐ Tijd traject bedraagt ongeveer	**tussen 15 en 30 minuten**
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Financiële tussenkomst door werkgever	**Neen**

☐ Tijd traject bedraagt ongeveer	**tussen 15 en 30 minuten**
Het traject van uw fietsroute gaat	**veelal via fietspaden**
Weersomstandigheden zijn	**gunstig: droog en weinig tot geen wind**
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Douche op uw werkplek	**Aanwezig**
Beveiligde parking op uw werkplek	**Aanwezig, zonder oplaadpunt**
Financiële tussenkomst door werkgever	**Ja**

☐ Geen van beide opties, liever met een ander vervoermiddel, zoals auto, bus, ...

Vorige Volgende

LimeSurvey

Hervat later

50%

Deze enquête is nu niet actief. Uw antwoorden kunnen niet worden opgeslagen.

Deel III: In wat volgt, stellen we 7 controlevragen om de invloed van bepaalde factoren nog beter te kunnen inschatten.

Speelt **het traject van uw fietsroute** een rol in uw mobiliteitskeuze?

Kies maximaal één antwoord

- [ ] Ja
- [ ] Neen

Speelt **de rijtijd van uw verplaatsing** een rol in uw mobiliteitskeuze?

Kies maximaal één antwoord

- [ ] Ja
- [ ] Neen

Speelt **de mogelijkheid om te douchen op uw werkplek** een rol in uw mobiliteitskeuze?

Kies maximaal één antwoord

- [ ] Ja
- [ ] Neen

Speelt **financiële tussenkomst door uw werkgever** een rol in uw mobiliteitskeuze?

Kies maximaal één antwoord

- [ ] Ja
- [ ] Neen

Speelt **de aanwezigheid van een beveiligde parking voor fietsen** een rol in uw mobiliteitskeuze?

Kies maximaal één antwoord

- [ ] Ja
- [ ] Neen

Speelt **het beschikbare type elektrische fiets** een rol in uw mobiliteitskeuze?

Kies maximaal één antwoord

- [ ] Ja
- [ ] Neen

Spelen **de weersomstandigheden** een rol in uw mobiliteitskeuze?

Kies maximaal één antwoord

- [ ] Ja
- [ ] Neen

Vorige

Volgende

LimeSurvey

Hervat later

62%

Deze enquête is nu niet actief. Uw antwoorden kunnen niet worden opgeslagen.

Wat is uw leeftijd?

Wat is uw geslacht?

Kies maximaal één antwoord

- [ ] Man
- [ ] Vrouw
- [ ] Andere
- [ ] Wil ik liever niet zeggen

Wat is uw hoogst behaalde diploma?

Kies maximaal één antwoord

- [ ] Geen diploma
- [ ] Lager onderwijs
- [ ] Secundair onderwijs
- [ ] Bachelor
- [ ] Master
- [ ] Doctoraat

Bezit u een elektrische fiets?

Kies maximaal één antwoord

- [ ] Ja
- [ ] Neen
- [ ] Neen, maar iemand van mijn gezin wel

Overweegt u de aankoop van een elektrische fiets voor het woon-werkverkeer?

Kies maximaal één antwoord

- ☐ Ja, een normale elektrische fiets
- ☐ Ja, een speedelec (elektrische fiets die tot 45 km/h kan gaan)
- ☐ Neen
- ☐ Neen, ik heb al een elektrische fiets
- ☐ Misschien

Hoeveel bent u maximaal bereid te betalen voor een elektrische fiets? (in €)

Welke factor(en) spelen een rol in uw keuze om (al dan niet) met een elektrische fiets naar het werk te rijden?

Vorige Volgende

LimeSurvey

Hervat later

75%

Deze enquête is nu niet actief. Uw antwoorden kunnen niet worden opgeslagen.

Om volledig te begrijpen welke factoren een rol spelen om met een elektrische fiets naar het werk te rijden, volgen nog enkele **korte vragen over die factoren.**

Is **financiële tussenkomst door uw werkgever** een bepalende factor bij uw mobiliteitskeuze?

Kies maximaal één antwoord

- [ ] Ja
- [ ] Neen

Is **het traject van uw fietsroute** een bepalende factor bij uw mobiliteitskeuze?

Kies maximaal één antwoord

- [ ] Ja
- [ ] Neen

Is de **de aanwezigheid van een beveiligde parking voor fietsen** een bepalende factor bij uw mobiliteitskeuze?

Kies maximaal één antwoord

- [ ] Ja
- [ ] Neen

Is **de rijtijd van uw verplaatsing** een bepalende factor bij uw mobiliteitskeuze?

Kies maximaal één antwoord

- [ ] Ja
- [ ] Neen

Zijn **de weersomstandigheden** een bepalende factor bij uw mobiliteitskeuze?

Kies maximaal één antwoord

- [ ] Ja
- [ ] Neen

Is **de mogelijkheid om u te verfrissen (douche) op uw werkplek** een bepalende factor bij uw mobiliteitskeuze?

Kies maximaal één antwoord

- [ ] Ja
- [ ] Neen

Is **het beschikbare type elektrische fiets** een bepalende factor bij uw mobiliteitskeuze?

Kies maximaal één antwoord

- [ ] Ja
- [ ] Neen

Vorige Volgende

LimeSurvey

Hervat later

87%

Deze enquête is nu niet actief. Uw antwoorden kunnen niet worden opgeslagen.

Wilt u graag op de hoogte gehouden worden over de resultaten van dit onderzoek?

Kies maximaal één antwoord

- [ ] Ja
- [ ] Neen

Indien ja, gelieve hieronder uw e-mailadres op te geven.

Heeft u verder nog opmerkingen of bedenkingen over elektrische fietsen in het woon-werkverkeer? Of dit onderzoek?

Vorige

Verzenden

LimeSurvey

Deze enquête is nu niet actief. Uw antwoorden kunnen niet worden opgeslagen.

Niet bewaard Your survey responses have not been recorded. This survey is not yet active.

Heel erg bedankt om deel te nemen aan dit onderzoek.

Corneel Casier, Student 2e Master Geografie, Universiteit Gent
Promotor: Prof. Dr. Frank Witlox, vakgroep Geografie, Universiteit Gent

geografie vakgroep Universiteit Gent

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8.3 Appendix C - Data frame responses

Table 12 shows the data frame of one respondent. The first column, 'STR', shows the number of the respondent combined with the number of the question. The column 'RES' shows a value of '1', if the respondent chooses this alternative and '0' if otherwise. The columns 'TIME' to 'FINANCIAL' represents the variable levels for each profile alternative. This is similar to Table 2, the only difference is the effect coding of the variables with two levels and the dummy coding for the variables with three levels. The last three columns shows the characteristic of the respondent. In this case a female, non e-bike owner, who is older than the average age of all respondents. For other respondents this table looks similar, only the columns 'STR', 'RES' and the last three columns differ. The full data frame for all respondents can be found in the digital attachments.

Table 12: Data frame of one respondent

STR	RES	TIME	TRAJECTORY	WEATHER	TYPE	SHOWER	PARKING	FINANCIAL	NONE	EBIKE	MALE	OLD
101	0	1	1	-1	1	-1	2	-1	-1	0	0	1
101	0	2	-1	-1	-1	1	2	-1	-1	0	0	1
101	1						0		1	0	0	1
102	0	2	-1	-1	-1	1	3	1	-1	0	0	1
102	1	3	-1	1	1	1	3	-1	-1	0	0	1
102	0						0		1	0	0	1
103	0	3	-1	-1	-1	-1	2	1	-1	0	0	1
103	1	3	-1	-1	-1	1	1	1	-1	0	0	1
103	0								1	0	0	1
104	0	3	-1	1	1	1	3	-1	-1	0	0	1
104	0	2	-1	-1	1	1	2	-1	-1	0	0	1
104	1						0		1	0	0	1
105	0	3	-1	-1	-1	1	1	1	-1	0	0	1
105	0	2	1	-1	-1	1	1	1	-1	0	0	1
105	1						0		1	0	0	1
106	0	3	1	-1	1	1	2	-1	-1	0	0	1
106	1	3	1	1	-1	-1	1	1	-1	0	0	1
106	0								1	0	0	1
107	0	1	-1	1	-1	1	2	-1	-1	0	0	1
107	0	3	1	-1	1	-1	3	-1	-1	0	0	1
107	1								1	0	0	1
108	1	2	1	1	-1	1	2	1	-1	0	0	1
108	0	1	1	1	-1	-1	2	1	-1	0	0	1
108	0								1	0	0	1
109	1	3	1	1	-1	-1	1	1	-1	0	0	1
109	0	1	-1	1	-1	1	1	-1	-1	0	0	1
109	0								1	0	0	1
110	0	2	-1	-1	1	1	2	-1	-1	0	0	1
110	1	2	-1	1	1	-1	2	1	-1	0	0	1
110	0						0		1	0	0	1
111	1	1	1	1	-1	-1	2	1	-1	0	0	1
111	0	2	-1	-1	-1	1	3	1	-1	0	0	1
111	0						0		1	0	0	1
112	0	2	1	-1	-1	1	1	1	-1	0	0	1
112	0	1	1	-1	1	-1	2	-1	-1	0	0	1
112	1						0		1	0	0	1
113	0	2	-1	1	1	-1	2	1	-1	0	0	1
113	1	3	-1	1	-1	1	1	-1	-1	0	0	1
113	0						0		1	0	0	1
114	0	3	1	-1	1	-1	3	-1	-1	0	0	1
114	0	3	-1	-1	-1	-1	2	1	-1	0	0	1
114	1						0		1	0	0	1
115	1	3	-1	1	-1	1	1	-1	-1	0	0	1
115	0	3	1	-1	1	1	2	-1	-1	0	0	1
115	0						0		1	0	0	1
116	0	2	-1	-1	-1	1	2	-1	-1	0	0	1
116	1	2	1	1	-1	1	2	1	-1	0	0	1
116	0						0		1	0	0	1

8.4 Appendix D - Data cleaning

When we check the data for respondents that did not fill in the survey truthfully, we checked this on three elements. The first one, being time to fill in the full survey. One respondent (number 143) filled in the survey sub five minutes. The second element, we checked were the control questions. Five respondents (numbers 54, 78, 79, 87, 109 and 123) filled in more than two control questions differently. The last element we checked in the data, was straight lining. Four respondents (number 7, 59, 65 and once again 143) respondents showed signs of this in their answers. This makes that ten respondents supposedly did not fill in the survey correctly. To see if excluding affect our model, we ran our model with and without them. Table 13 and 14 show the results of this.

When we compare the two models, one with all respondents (Table 13) and one without the removed respondents (Table 14), we see no clear differences. This makes us decide that excluding the ten respondents that did not fill in the survey truthfully, does not affect our data. We decide to leave them out in all further analyses in this investigation.

Table 13: summary logit model with all respondents

	Coefficient (= B)	**Standard Error**	**Wald**	**DF**	**Significance (p-value)**
Intercept	-0,614	0,079	59,756		0,000
Time			121,108	2	0,000
• **15 minutes** • **Between 15 and 30 minutes** • **30 minutes**	0,338 0,167 0	0,098 0,090			
Trajectory	0,273	0,035	62,412	1	0,000
Weather	0,517	0,033	245,654	1	0,000
Type	0,588	0,056	111,739	1	0,000
Shower	0,148	0,048	9,476	1	0,002
Parking			73,235	2	0,000
• **Present *with* possibility to load battery** • **present *without* possibility to load battery** • **Parking: absent**	0,783 0,037 0	0,108 0,094			

Financial intervention by employer	0,551	0,054	104,601	1	0,000
No-choice parameter	-0,879	0,095	85,73	1	0,000

Table 14: summary logit model without removed respondents

	Coefficient (= B)	Standard Error	Wald	DF	Significance (p-value)
Intercept	-0,649	0,083	61,789		0,000
Time			105,692	2	0,000
• **15 minutes** • **Between 15 and 30 minutes** • **30 minutes**	0,375 0,197 0	0,102 0,094			
Trajectory	0,280	0,036	60,820	1	0,000
Weather	0,528	0,036	237,152	1	0,000
Type	0,587	0,034	102,763	1	0,000
Shower	0,143	0,050	8,168	1	0,004
Parking			70,861	2	0,000
• **Present *with* possibility to load battery** • **present *without* possibility to load battery** • **Parking: absent**	0,802 0,042 0	0,112 0,098			
Financial intervention by employer	0,557	0,056	98,714	1	0,000
No-choice parameter	-0,817	0,098	69,075	1	0,000

8.5 Appendix E - Gender

Coefficients:

	Estimate	Std. Error	z value	Pr(>|z|)	
(Intercept)	-0.74047	0.04255	-17.402	< 2e-16	***
TIME15	0.32584	0.09368	3.478	0.000505	***
TIME30	-0.20787	0.06544	-3.176	0.001491	**
TRAJECTORY_BIKEROAD	0.26582	0.04730	5.620	1.91e-08	***
WEATHER_GOOD	0.54503	0.04526	12.042	< 2e-16	***
TYPE_NORMAL	0.75964	0.08044	9.443	< 2e-16	***
SHOWER_YES	0.09251	0.06607	1.400	0.161422	
PARKING_WITH_CHARGE	0.56588	0.08287	6.828	8.60e-12	***
PARKING_WITHOUT_CHARGE	-0.25026	0.07115	-3.517	0.000436	***
FINANCIAL_YES	0.65950	0.07757	8.502	< 2e-16	***
NONE	-0.56507	0.04255	-13.280	< 2e-16	***
MALE	-0.21614	0.06989	-3.093	0.001985	**
TIME15:MALE	-0.32514	0.14226	-2.285	0.022284	*
TIME30:MALE	0.04557	0.10113	0.451	0.652298	
TRAJECTORY_BIKEROAD:MALE	0.04391	0.07333	0.599	0.549269	
WEATHER_GOOD:MALE	-0.02698	0.07001	-0.385	0.699937	
TYPE_NORMAL:MALE	-0.37539	0.11676	-3.215	0.001305	**
SHOWER_YES:MALE	0.14014	0.10154	1.380	0.167541	
PARKING_WITH_CHARGE:MALE	-0.08838	0.12674	-0.697	0.485624	
PARKING_WITHOUT_CHARGE:MALE	0.01759	0.10930	0.161	0.872173	
FINANCIAL_YES:MALE	-0.20954	0.11285	-1.857	0.063344	.
NONE:MALE	-0.20961	0.06989	-2.999	0.002708	**

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

We see that multiple part-worths are significant here. The factor levels, time around 15, time around 30 minutes, type of e-bike and the 'none of these'-alternative are significant when comparing male and female respondents.

8.6 Appendix F - E-bike ownership

```
Coefficients:
                              Estimate Std. Error z value Pr(>|z|)    
(Intercept)                  -0.824147   0.042883 -19.219  < 2e-16 ***
TIME15                        0.174086   0.089951   1.935 0.052947 .  
TIME30                       -0.192634   0.064290  -2.996 0.002733 ** 
TRAJECTORY_BIKEROAD           0.276182   0.046428   5.949 2.70e-09 ***
WEATHER_GOOD                  0.570376   0.044231  12.895  < 2e-16 ***
TYPE_NORMAL                   0.478204   0.073494   6.507 7.68e-11 ***
SHOWER_YES                    0.180637   0.064842   2.786 0.005339 ** 
PARKING_WITH_CHARGE           0.519288   0.079929   6.497 8.20e-11 ***
PARKING_WITHOUT_CHARGE       -0.242595   0.069840  -3.474 0.000514 ***
FINANCIAL_YES                 0.507657   0.071232   7.127 1.03e-12 ***
NONE                         -0.595710   0.042883 -13.892  < 2e-16 ***
EBIKE                         0.002947   0.069022   0.043 0.965948    
TIME15:EBIKE                  0.028918   0.144031   0.201 0.840876    
TIME30:EBIKE                  0.002151   0.101556   0.021 0.983103    
TRAJECTORY_BIKEROAD:EBIKE     0.005374   0.073443   0.073 0.941664    
WEATHER_GOOD:EBIKE           -0.102309   0.070264  -1.456 0.145375    
TYPE_NORMAL:EBIKE             0.287945   0.120253   2.394 0.016644 *  
SHOWER_YES:EBIKE             -0.091442   0.102041  -0.896 0.370182    
PARKING_WITH_CHARGE:EBIKE     0.006821   0.127601   0.053 0.957370    
PARKING_WITHOUT_CHARGE:EBIKE  0.008788   0.109479   0.080 0.936022    
FINANCIAL_YES:EBIKE           0.140191   0.116106   1.207 0.227265    
NONE:EBIKE                   -0.123090   0.069022  -1.783 0.074530 .  
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Only the type of e-bike is significant here, when controlling for e-bike owners.

8.7 Appendix G - Age

```
Coefficients:
                            Estimate Std. Error z value Pr(>|z|)    
(Intercept)                -0.864253   0.049545 -17.444  < 2e-16 ***
TIME15                      0.355108   0.101163   3.510 0.000448 ***
TIME30                     -0.254262   0.070442  -3.610 0.000307 ***
TRAJECTORY_BIKEROAD         0.278891   0.051506   5.415 6.14e-08 ***
WEATHER_GOOD                0.612366   0.048783  12.553  < 2e-16 ***
TYPE_NORMAL                 0.659116   0.085367   7.721 1.15e-14 ***
SHOWER_YES                  0.148069   0.072016   2.056 0.039778 *  
PARKING_WITH_CHARGE         0.584802   0.089286   6.550 5.76e-11 ***
PARKING_WITHOUT_CHARGE     -0.327174   0.077311  -4.232 2.32e-05 ***
FINANCIAL_YES               0.701780   0.081845   8.575  < 2e-16 ***
NONE                       -0.818903   0.049545 -16.529  < 2e-16 ***
OLD                         0.075488   0.067589   1.117 0.264056    
TIME15:OLD                 -0.337136   0.140895  -2.393 0.016720 *  
TIME30:OLD                  0.129621   0.099577   1.302 0.193011    
TRAJECTORY_BIKEROAD:OLD     0.005363   0.072025   0.074 0.940649    
WEATHER_GOOD:OLD           -0.163638   0.068766  -2.380 0.017330 *  
TYPE_NORMAL:OLD            -0.133238   0.116453  -1.144 0.252567    
SHOWER_YES:OLD             -0.012356   0.100150  -0.123 0.901811    
PARKING_WITH_CHARGE:OLD    -0.123249   0.125017  -0.986 0.324200    
PARKING_WITHOUT_CHARGE:OLD  0.170464   0.107749   1.582 0.113640    
FINANCIAL_YES:OLD          -0.277170   0.112624  -2.461 0.013855 *  
NONE:OLD                    0.337276   0.067589   4.990 6.04e-07 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

We see that the factors, time around 15, weather conditions, financial aid by employer and ‘none of these’ option are significant when we compare young and older respondents.