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An Analysis of Trip Preferences among E-bike Users in Commuting: Evidence from an Online Choice-based Conjoint Experiment

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The present study reports on the preferences among e-bike users for commuting trips. An online survey with sixteen choice-based conjoint questions was conducted in March 2020 amongst 144 e-cyclists and non e-cyclists in Flanders (Belgium). Their choices were analysed using a no-choice binomial logit model. The impact of the following factors showed to be most important: weather conditions, trip time, type of e-bike, and financial support by the employer. The effect on e-bike users of factors such as cycling infrastructure, secure parking, and shower facilities at the workplace seems more limited. Based on the difference between male and female respondents, trip time and type of e-bike differed significantly. The only significant difference between e-bike owners and non e-bike owners was the type of e-bike. Trip time, weather conditions and financial intervention differed significantly between the young and old age group. Our findings suggest that policymakers should focus on investments in e-bikes, such as cycling infrastructure, mileage allowance and facilities at the workplace to make this a sustainable and socially inclusive mode of transport.

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1. Introduction

The last 15 years have seen the rise of a broad range of new methods of transport. In several cities, e-scooters, cargo bikes, e-steps, e-skateboards, monowheels, car- and bike-sharing systems have popped up. In particular e-bikes have become well visible in our daily lives - on the streets, in newspapers, in magazines, and in advertisements. An e-bike is a bicycle-like vehicle with functional pedals that power an electrical motor (Fishman & Cherry, 2016). Because of the support this gives, riding one requires less effort. The reduction in effort is the main advantage. Reaching faster speeds and covering longer distances becomes easier. E-bikes can be pedelec (where the electrical motor only responds to movement of the pedals) or non-pedelec (where pedals are present but the electrical motor can be switched on using, e.g., a throttle on the handlebars;). A specific type of pedelecs are the so-called speed pedelecs that according EU 168/2013 offer pedal assistance up to 45 km/h, whereas regular e-bikes give electrical assistance up to 25 km/h. Riding a speed pedelec in Belgium requires drivers to have a driving license (minimum category AM), to wear a helmet and acquire a licence plate for the bicycle and a specific insurance (Rotthier et al., 2017).

The 21st century boom in e-bikes contrasts with the history of e-bikes that dates back to the early 19th century. Improvements in battery quality and lower prices have made this shift possible. The increase in interest in e-bikes can be seen in the number of sales (e.g., Fishman & Cherry, 2016). E-bikes represent one of the fastest growing segments in the transport market. There has been a clear rise in purchases of pedelec type e-bikes in European countries in the last decade (2010-2020). The current expansion of the European e-bike market reflects the Chinese experience with non-pedelec e-bikes of the previous decade (2001-2010) (e.g., Astegiano et al., 2017; Zagorskas & Burinskienė, 2020). In 1998, Chinese factories assembled a mere 40,000 e-bikes. By 2005, the number had grown to more than ten million. After this exponential growth, the market kept growing, albeit more steadily (Cherry & Cervero, 2007; Weinert et al., 2007).

Rising sales numbers played a role in the more general acceptance of e-bikes as a functional mode of transport. The distances people cover in commuting (i.e., the regular journey between work and home) and the range that an e-bike can cover (i.e., with a fully charged battery) are of equal significance. The distance people can easily cover with a pedelec and non-pedelec type e-bike is, depending on the local context, estimated to be between 5 and 15 km (Astegiano et al., 2017; Berjisian & Bigazzi, 2019; Cairns et al., 2017; Fyhri & Fearnley, 2015; IMOB, 2020; Lopez et al., 2017; Rotthier et al., 2017; Zagorskas & Burinskienė, 2020). Van den Bergh et al. (2018) found that users prefer e-bikes mostly for medium length trips (i.e., 14 km). In Flanders, the northern Dutch-speaking region of Belgium, approximately more than 60% of the working population live closer than 15 km to their work and around 68% live closer than 20 km (IMOB, 2020).

The current modal share of e-bikes for commuting purposes is 2.4% in Flanders (IMOB, 2020). This shows an untapped potential for e-bikes. Simultaneously, the calls for a more sustainable society become louder and louder (e.g., UN, 2019). To answer these, policy makers have to take multiple actions. One is to encourage the use of more sustainable travel modes, such as public transport, walking, cycling - and e-bikes. Investment in infrastructure and subsidies are the two main actions they can take to reach this goal (McQueen et al., 2020). Furthermore, we note that policy makers have seen the potential of e-bikes, and have high expectations of this durable transport mode in improving accessibility and liveability in cities and rural villages (Fishman & Cherry, 2016; Kazemzadeh & Ronchi, 2022).

E-cycling has been the topic of some research, the focus of which has been on socio-demographics (e.g., Cherry & Cervero, 2007; de Haas et al., 2021; Jahre et al., 2019), health (e.g., Bourne et al., 2018; Hansen et al., 2018), the impact on sustainability (e.g., Fyhri & Sundfør, 2020; McQueen et al., 2020; Sun et al., 2020), and the motives of e-bike users (e.g., Jones et al., 2016; Popovic et al., 2014). Multiple authors have carried out studies on the use of e-bikes in commuting. Jahre et al.

(2019) by focusing on socio-demographic factors, frequency and distances, Lopez et al. (2017) by looking at GPS traces, Nematchoua et al. (2020) by researching potential modal shift, Plazier et al. (2017) by investigating motives, behaviours and experiences of commuting e-bikers and Zijlstra (2016) by exploring heterogeneity in electric bicycle preferences. However, our understanding of the conditions under which people will opt for an e-bike remains limited, especially amongst the group of commuters, where this untapped potential exists (Kazemzadeh & Ronchi, 2022). More knowledge on this topic could help policymakers to determine how to improve the likelihood people use an e-bike to go to work. The present study aims to identify and quantify the factors that influence the use of e-bikes in commuting. To do so, we collected data using an online survey completed by e-bike and non e-bike users in Flanders, Belgium. This information is valuable for policy makers as well, since it enables them to know how different interventions impact the behaviour of (potential) e-cyclists.

The remainder of the study has the following structure. Section 2 summarises the limited literature on e-bikes and possible factors that influence this transport mode. Section 3 presents details about the methodology used. Using an online choice-based conjoint (CBC) experiment including a no-choice option, we measured the relevance of multiple influencing factors on the use of e-bikes. Participants were required to indicate their preferred set of influencing factors from two sets, while still allowing them to choose another transport mode, the so-called no-choice alternative. We analysed the data using a no-choice binomial logit model. The results, presented in Section 4, allowed us to establish the factors with the largest impact on people using, or thinking about using, an e-bike in commuting - and how policy makers and employers can influence these. Section 5 concludes the study.

2. E-bikes and commuting

A broader understanding of e-bikes is useful in knowing what factors influence the choice for e-bikes in commuting. In the following sections, we discuss the characteristics of e-bikes and the contextual framework (social, demographic, economic, and policy-related factors).

2.1 E-bike journeys

The main reason people use e-bikes is the electrical assistance. This makes it easier to take longer trips and to cover hilly terrain. An e-bike can more easily cover larger distances and hills in a physically less strenuous way. At the same time, an e-bike offers many of the same benefits as motorised transport such as mopeds and cars, for example a larger range and greater flexibility (Cairns et al., 2017; Dill & Rose, 2012; Fishman & Cherry, 2016; Fyhri & Fearnley, 2015; Plazier et al., 2017; Popovich et al., 2014; Rotthier et al., 2017).

The increase in cycling speed makes it more possible to travel at speeds comparable with local public transport and rush hour urban driving. Another advantage is the e-bike's energy efficiency. Dave (2010) and Rotthier et al. (2017) found that this is better than most modes of transport (except a traditional bike). The e-bike is therefore environmentally superior to other motorised modes of transport. A shift from car and public transport to e-bikes will be beneficial for the environment, public health, and other motorists (Fyhri & Fearnley, 2015). An additional advantage of e-bikes is the impact they have on the health of users. Studies have shown that e-cyclists have more physical exercise because they ride longer distances and take more trips (An et al., 2013; Fyhri & Fearnley, 2015). Such trips, with the assistance of a battery, compensate for the smaller effort undertaken per kilometre than when a conventional bicycle is used (Berjisian & Bigazzi, 2019; Bourne et al., 2018; Hansen et al., 2018). Health benefits are therefore an important underlying factor in the choice to e-bike, especially for older people (Jones et al., 2016). It is important to note that most studies have found that e-cyclists need a sufficient safe cycling infrastructure; otherwise, insecurity in traffic can negate physiological and psychological advantages (e.g., Hansen et al., 2018).

Although e-bike use has multiple benefits, it inevitably has disadvantages. As with normal bikes, e-bikes offer no immediate solution when a person needs to transport larger loads or when the weather conditions are unfavourable (e-bike users have no protection against any form of precipitation, like rain, hail or snow). Riding an e-bike outside urban areas will evidently be slower than motorised transport (Heinen, 2010). Negative aspects cited by e-bike users included a lack of security (theft and damage of e-bike), safety concerns, a sense of unwieldiness (due to the heavy battery and electrical motor), and range anxiety (Edge et al., 2018; Fyhri et al., 2017; Jones et al., 2016; Popovich et al., 2014; Van Cauwenberg et al., 2019). These feelings are associated with insufficiently adjusted cycling infrastructure. Users noted that complex traffic nodes, wells, bumps in the road, and no entirely open cycle-only routes because of the presence of parked cars makes e-cycling unsafe. A last element that users often see as a disadvantage is the lack of safe, adjusted parking, which is not always possible for the heavier e-bikes. This is especially linked with theft concerns (Edge et al., 2018; Rotthier et al., 2017).

In 2019, people in Flanders (the Dutch-speaking part of Belgium) e-biked mainly to go to work (31%) and to go shopping (26.8%). The modal share (the number of trips involving a certain transport mode relative to all trips made in an area) of e-bikes in commuting has evolved over the years, from 1.0% in 2015, 1.6% in 2016, 2.3% in 2017, to 4.6% in 2018 (IMOB, 2020).

2.2 *Influencing factors in e-bike use*

The factors that influence e-bike use will now be examined. As with other modes of transport, socio-economic and demographic characteristics play a part. A shift has taken place in the age of e-bike users. Some studies have shown that the average age of e-bike users tend to be higher than the average population (Cherry & Cervero, 2007; MacArthur et al., 2014; Simsekoglu & Klöckner, 2019; Wolf & Seebauer, 2014), while others have found that there are no significant differences (An et al., 2013; Fyhri & Fearnley, 2015). Previously, e-bikes were used solely by older adults. Now, all age categories accept and use them (de Haas et al., 2021; Fishman & Cherry, 2016). Data from Belgium show this trend clearly. In 2015, e-bike users were almost entirely (96%) in the older age categories (older than 46 years). Three years later, the spread was much wider: 9% were in the 18-25 category, 10% of the e-bikers were between 26 and 35, and 13% were between 36 and 45. The share of e-bike users who were older than 46 had fallen to 68% (IMOB, 2020).

Studies on the gender of e-cyclists have suggested that most e-cyclists are predominantly male. MacArthur et al. (2014) and Johnson and Rose (2013), respectively, found that 85% and 71% of users were men. Fyhri and Fearnley (2015) concluded that although users are mostly male, e-bikes have a greater influence amongst females. In a Chinese study, An et al. (2013) observed that there were no significant differences between genders. In Flanders, 41.3% of e-bike users are male and 58.7% are female (IMOB, 2020).

The educational background of e-cyclists is similar across different studies that have examined this topic. E-bike users often have higher educational attainments than conventional cyclists. MacArthur et al. (2014) stated that 34% of e-bikers have a graduate degree. Cherry and Cervero (2007) and Johnson and Rose (2013) found that e-bike users in China and Australia have significantly a higher educational background than conventional cyclists. Closely related to the educational background of e-bikers is their income. Cherry and Cervero (2007) and Johnson and Rose (2013) discovered that the incomes of e-bike users in China and Australia were significantly higher than those of conventional cyclists. When looking at car and bike ownership for e-cyclists, Cherry et al. (2016) demonstrated that car ownership amongst Chinese e-bike users increased and conventional bike ownership decreased the longer they used an e-bike. Ling et al. (2015) predicted that "e-bikes may be a key vehicle in the motorisation pathway toward car ownership."

Knowledge of the modal shift to e-bikes (the change from other modes of transport to e-bikes). is useful in policymaking and in assessments of their environmental impact (Kazemzadeh & Ronchi, 2022; Sun et al., 2020; Wolf & Seebauer, 2014). Depending on the local context, results differ between studies, yet certain trends have become apparent. 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), but they seldom generate a modal shift from cars (An et al., 2013; Berjisian & Bigazzi, 2019; de Haas et al., 2021; Kroesen, 2017). They sometimes offer an alternative to car journeys of short duration. Modal share is also important for establishing the current and future potential of e-bikes. The percentages for all uses evolved from 0.9% in 2016, 1.1% in 2017, 1.4% in 2018, to 2.4% in 2019. For reasons of comparison, the modal share in Flanders of conventional bicycles was 14.4%, 64.7% for cars, and 12.3% for pedestrians (IMOB, 2020). Policies regarding e-bikes have clearly had an impact on modal share figures. Policy actions are therefore the last influential factor we will discuss here. Policymakers have a two-fold role. In the first place, they have to create a legislative framework for e-bikes. The questions they need to address include the following: Is a driving licence needed? What is the maximum permitted speed for e-bikes? Where can e-bikers ride on the road? Do they need a licence plate or insurance?

In addition to answering those questions, policymakers can promote or constrain certain transport modes. The Belgian and Flemish governments try to encourage people into using an e-bike in a number of ways. The first is by coaxing firms to lease e-bikes to their employees. The costs incurred for this (often for a speed pedelec) were 120% tax deductible as professional expenses for self-employed people and company managers until the end of December 2019. From 2020 onwards, the rate was reduced to 100%. In 2014, 75% (between 40,000 and 50,000 in total) of leased bicycles were e-bikes. The second was in the form of a bicycle allowance (a fixed amount of money an employee receives for each kilometre that is cycled to work). This is very high in Belgium (€0.24 per kilometre travelled). Several studies have shown that these have a substantial effect in attracting people to e-bike commuting (IMOB, 2020; Stewart et al., 2015; Vandenbulcke et al., 2011; Vanoutrive et al., 2009; Wardman et al., 2007).

Before presenting our methodology, we briefly discuss a number of similar papers that have investigated the impact of factors influencing e-bike use in general. Nematchoua et al. (2020) conducted a revealed preference (RP) study of university staff and students in Liège (Belgium). They found that for both e-bike and conventional bicycle riders, the lack of safe cycle lanes was a major hindrance. Topographical relief was far less a limitation for e-bikes than for conventional bicycles. Additionally, the lack of parking or higher priced parking was often stated to be a burden. The stated preference study of van den Bergh et al. (2018) revealed that (along with transport modes such as solar and conventional bikes) bad weather conditions had a negative effect on the decision to use an e-bike. Other circumstances that had a negative effect on e-bikes were dark lightning conditions and an insufficient quality of cycling infrastructure. The authors learnt that secure parking had a small positive effect on the likelihood of choosing to use an e-bike. Good quality cycling lanes were more important for e-bikers. In a stated preference (SP) study, Zijlstra (2016) focused on the marketing sales aspect of e-bikes, and concluded that the range and price of an e-bike were the most important attributes. Different model types, speeds, and warranties were less important. A range of approximately 100 km, a price of €2,000, a city type model, high speed, and a warranty of three years were the most preferred attribute levels. Astegiano et al. (2017) and Lopez et al. (2017) concluded that e-cyclists used cycleways on average more than conventional cyclists. The main reason for this was probably the longer-range distances e-bikes can cover. For conventional bicycles and e-bikes, the positive effects of good quality cycling lanes have been researched on many occasions (e.g., Buehler & Pucher, 2012; Howard & Burns, 2001; Mertens et al., 2016; Mueller et al., 2018; Schepers et al., 2021; Simsekoglu & Klöckner, 2019; Stewart et al., 2015; Vanoutrive et al., 2009; Wooliscroft & Ganglmair-Wooliscroft, 2014).

Overall, in addition to the multivariate studies discussed above, RP & SP surveys provide insights into the importance of various attributes of e-bikes compared with other modes of transport. However, current studies do not provide information on the factors that influence the use of e-bikes in commuting. In our study, we attempt to fill this gap (Kazemzadeh & Ronchi, 2022). Does a mileage allowance have a similar effect on e-cyclists as on conventional cyclists? How do rainy weather conditions affect the use of e-bikes? What is the effect of cycling lanes on e-bike use? Are the same attributes equally important for users of conventional bikes as e-bicyclists, or do differences exist between them? To the best of our knowledge, these questions have not been subject to a great deal of attention.

3. Methodology

We conducted an online SP survey in March 2020 after recruiting working adults in Flanders, Belgium. SP refers to a family of techniques which use individual respondents' statements about their preferences in a set of options to estimate utility functions (Kroes & Sheldon, 1988). We used here a specific form of SP survey, i.e. a CBC. The objective of this statistical technique is to determine what combination of a limited number of attributes is most influential on respondent choice for a specific product or service. We choose this since it allows us to estimate the psychological trade-offs that a respondent makes when evaluating multiple attributes together, while mimicking realistic choices and uncovering real and hidden drivers that are unknown to the respondents themselves (Witlox & Vandaele, 2005; Wooliscroft & Ganglmair-Wooliscroft, 2014). We targeted a sample of 100 commuting respondents, a number that is in accordance with the basic rule of Johnson & Orme (Orme, 1998) for the number of respondents and a minimum amount of choice situations in a CBC with 16 questions (Green & Rao, 1971; Johnson et al., 2013; LaVielle & Jeavons, 2012). Potential participants were invited to fill out the survey through a range of social media. A total of 154 respondents filled in the full survey. We removed those respondents who were "straight lining," that is, providing the same answer to each question, and one who filled in the full survey in an unrealistically short amount of time (less than five minutes). Additionally, we removed those people who did not answer the two sets of seven control questions appropriately. We assumed they were not interested in the survey. As a result of these measures, we retained 144 valid responses.

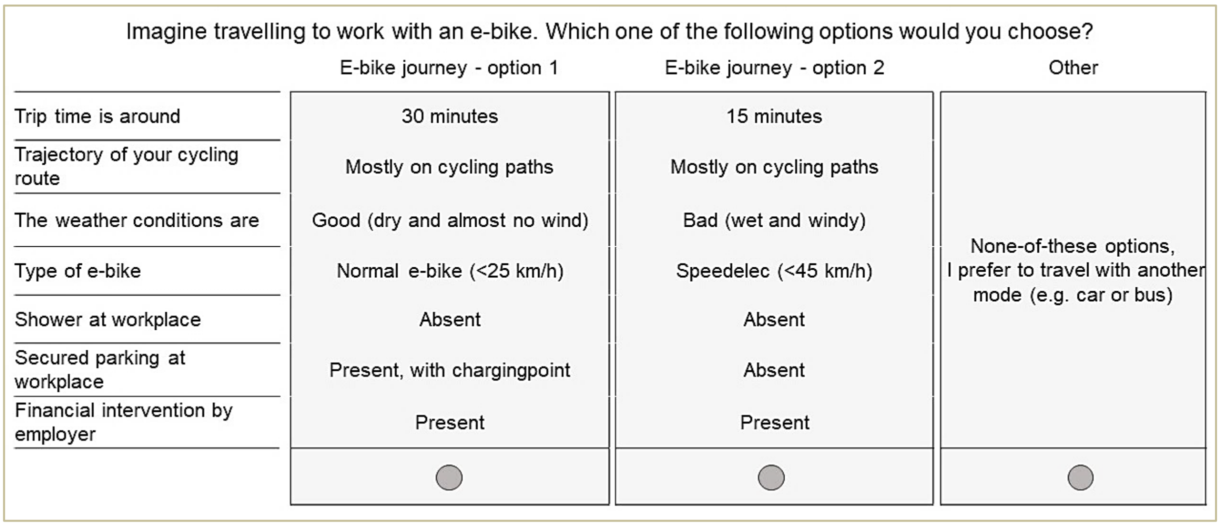
The CBC questions asked the respondents to indicate their preferred transport mode for 16 choice sets consisting of two alternative e-bike commute trips and a no-choice option, which was described as: "doing this commute trip using a mode of transport other than an e-bike." The profiles were composed of the levels of seven attributes representing hypothetical e-bike commute trips. The basis for the choice of these variables was similar research and the specific scope of the present study, namely the use of e-bikes in commuting and the specific questions that had emerged in the analysis of the literature. E.g. impact of the type of e-bike, a mileage allowance, rainy weather conditions, presence of cycling lanes or the impact of facilities at the workplace.

The attributes were: trip time (closely related to distance; e.g., van den Bergh et al., 2018), cycling infrastructure (e.g., Nematchoua et al., 2020; Simsekoglu & Klöckner, 2019; van den Bergh et al., 2018), weather conditions (e.g., Goldmann & Wessel, 2020; Simsekoglu & Klöckner, 2019; van den Bergh et al., 2018), type of e-bike (Zijlstra, 2016), and facilities at the workplace (e.g., showers, secure parking, and financial incentives, such as a mileage allowance; van den Bergh et al., 2018). Table 1 shows these attributes and their corresponding levels. The attributes "trip time" and "secure parking at the workplace" have three categorical variables ("15 minutes," "between 15 and 30 minutes," and "30 minutes" for the former and "present with option to charge battery," "present without option to charge battery," and "absent" for the latter). The five other attributes have two different categorical variable levels only.

Figure 1 presents a screenshot of a choice set as presented in the survey. This shows no difference between the variable levels for "trajectory," "shower" and "financial intervention by employer" in the two e-bike journey profiles. In other words, the levels of those three attributes were constant. We did this to limit the cognitive burden of the respondents. The levels of the other four attributes differed (Kessels et al., 2017; Van Acker et al., 2020). We determined these using the Fedorov algorithm, which selects the 16 profiles that represent the most optimal set of profiles in a CBC and generates a D-Optimal design (Fedorov, 1972). This minimises the generalised variance of the estimated regression coefficients (Aizaki & Nishimura, 2008; Miller & Nguyen, 1994; Rose & Bliemer, 2009). Next, the 16 profiles were duplicated and randomly combined so that 16 questions arose with each profile being present in two different questions (option 1 and option 2 once each) (Aizaki & Nishimura, 2008). Appendix B displays the full choice set part of the survey with the real-choice partial profiles, and provides more information on the design of the CBC.

Table 1. Seven Attributes and Their Levels in the E-bike CBC

Attribute	Level 1	Level 2	Level 3
Trip time	15 min.	Between 15 and 30 min.	30 min.
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 (up to 25 km/h)	Speed pedelec (up to 45 km/h)	
Shower at workplace	Present	Absent	
Secure parking at workplace	Present, with option to charge battery	Present, without option to charge battery	Absent
Financial intervention by the employer	Yes	No	


Imagine travelling to work with an e-bike. Which one of the following options would you choose?

	E-bike journey - option 1	E-bike journey - option 2	Other
Trip time is around	30 minutes	15 minutes	None-of-these options, I prefer to travel with another mode (e.g. car or bus)
Trajectory of your cycling route	Mostly on cycling paths	Mostly on cycling paths	
The weather conditions are	Good (dry and almost no wind)	Bad (wet and windy)	
Type of e-bike	Normal e-bike (<25 km/h)	Speedelec (<45 km/h)	
Shower at workplace	Absent	Absent	
Secured parking at workplace	Present, with chargingpoint	Absent	
Financial intervention by employer	Present	Present	

Figure 1. Example Choice Set CBC (translated from Dutch to English)

Additionally, we added the no-choice option to each choice set. All respondents received the same CBC, consisting of the same 16 choice sets. To analyse the respondents' choices, we used a binary logistic regression including the none-of-these option - the so-called no-choice binomial logit model (Haaijer et al., 2001; Train, 2009). The first reason we chose this model was our dichotomous dependent variable. This is one of the assumptions for a binary logistic regression. The preference of the interviewed person for the fictive products/scenarios is binary. A respondent prefers a certain profile or not. There are only two options for a respondent; either a respondent chooses a certain alternative or they do not (Hosmer & Lemeshow, 2000; McFadden, 1974; Rose & Bliemer, 2009; Train, 2009). The second reason was that we wanted to know the importance of the different variables and variable levels. A logistic regression estimates the coefficient of the different factors combined in a profile. Having those coefficients helps to determine which factors had the largest influence on the choice of a respondent, and to determine what profile had the highest preference (and the lowest). Furthermore, the likelihood of the none-of-these option could be estimated (Hauber et al., 2016; Hosmer & Lemeshow, 2000; Lannoo et al., 2018; Train, 2009). The third reason was that the model allowed the inclusion of the none-of-these option. This made it easier to estimate the coefficients and to give a better predictive fit than not including it or using a nested logit model (Haaijer et al., 2001; Lannoo et al., 2018; Van Acker et al., 2020).

We assumed normally distributed preference parameters without correlations between attributes, which is a common practice in choice modelling (Balbontin et al., 2019; Hou et al., 2019; Van Acker et al., 2020). These random parameters accommodate unobserved heterogeneity in the respondents' preferences. Coefficient estimates corresponding to the last level of an attribute are calculated as the minus of the other variable level when two levels are present (effect coding). When three levels are present, the third level has a value of 0, since we used dummy coding for the variable with three levels. What is also important is the interpretation of the results, the levels of one attribute should not be compared with the levels of other attributes; they should only be compared with the same attribute. For comparisons between different attributes, see Figure 4.

An extra advantage of this methodology was that it allowed us to split our data in two groups to determine if there were differences between them in terms of gender, age, and e-bike ownership. Dane et al. (2020) found that sociodemographic factors significantly affected e-bike use. We calculated the coefficients of each group and control if the results differed significantly (Allison, 1999). The making of two groups for gender (male and female) and e-bike ownership (those who owned an e-bike and those who did not) was straightforward. We separated the respondents into two groups based on age by using the mean age (i.e., 38.8 years) as a boundary.

4. Results & Discussion

At the start of the survey, we asked multiple general and commute-related questions of the sample group. Table 2 presents an overview of the answers to these questions. Figures 2 and 3 display the home and work locations of the respondents. A majority of these worked in the city of Ghent.

We see in Table 2 that e-bike owners were similar in number to the Flanders average (40%). There were significantly more women and higher educated respondents than there are in the average population. The modal split was fairly representative, yet we again saw a large group of e-bike users, possibly because they were interested in filling in the questionnaire. The commute distances were in line with those travelled by the general Flemish population (IMOB, 2020). Overall, although the sample showed a certain bias, it was again reasonably representative. However, this was not a problem because the findings were not intended to be generalised.

The 2,304 choices made in the 144 valid survey returns resulted in 1,872 preferences for e-bike commute trips (81.25%) versus 432 no-choices (18.75%) for journeys via another transport mode (the no-choice option). This result may be explained by the fact that most of the respondents probably had a prior interest in e-bikes (since they voluntarily completed a survey on this topic). It should therefore be interpreted with caution. It might be that respondents chose this option as a way-out because the two alternatives were similarly good or bad in their eyes (Johnson & Orme, 1996; Kessels et al., 2017; Van Acker et al., 2020). Additionally, the no-choice parameter was distinctly negative. This confirmed our assumption that the respondents were very interested in using an e-bike for their commute.

Table 2. General and E-bike Journey Characteristics (n = 144 Respondents)

Variable	Categories	Number	%
Gender	Male	59	41,0
	Female	85	59,0
Modal share in commute (main travel mode)	Car (as driver)	46	31,9
	Car (as passenger)	0	0
	Train	14	9,7
	Tram	3	2,1
	Bus	1	0,7
	Bicycle	40	27,8
	E-bike	38	26,7
	On foot	1	0,7
	Other	1	0,7
Educational level	No diploma	0	0
	High school	20	13,9
	Bachelor	57	39,6
	Master	54	37,5
	PhD	11	7,6
E-bike ownership	Owns an e-bike	57	39,6
	Does not own an e-bike	76	52,8
	Somebody in family owns an e-bike	11	7,6
Future willingness e-bike ownership	Already have an e-bike	55	38,2
	Want to acquire a normal e-bike (v < 25 km/h)	20	13,9
	Want to acquire a speed pedelec (v < 45 km/h)	8	5,7
	Want maybe to acquire an e-bike (either type)	20	13,9
	Does not want to acquire an e-bike	41	28,5
Age	18-24 years	25	17,4
	25-34 years	28	19,4
	35-44 years	29	20,1
	45-59 years	53	36,8
	N.A.	9	6,3
Commute trip distance	0-6 km	50	34,7
	7-12 km	37	25,7
	13-24 km	27	18,8
	>25 km	29	20,1
	N.A.	1	0,7

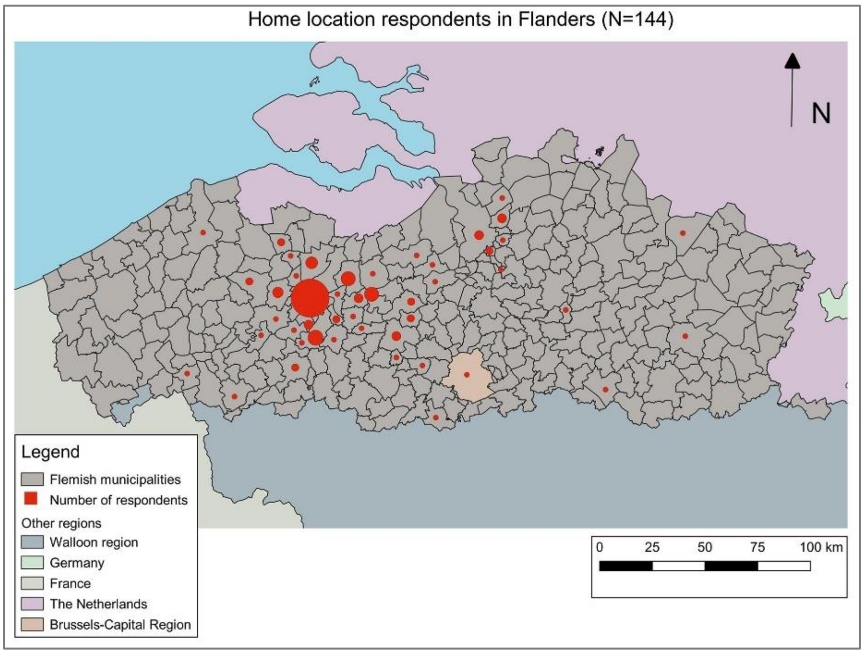


Figure 2. Home Location of Respondents

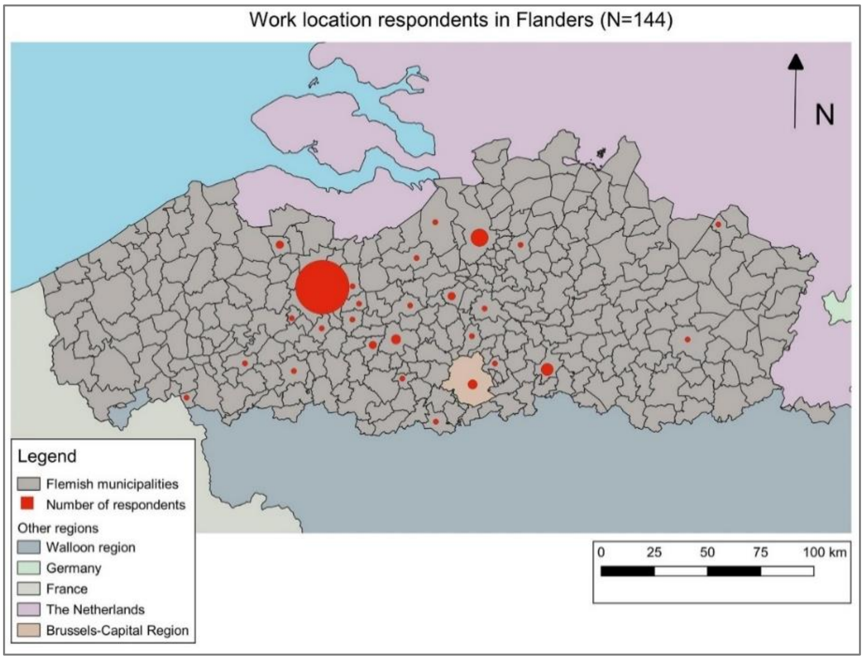


Figure 3. Work Location of Respondents

Table 3. No-choice Binomial Logit Model Estimates

Term	Coefficient (= B)	SE	Wald	DF	Significance (p-value)
Intercept	-0,649	0,083	61,79		< 0,001
Trip time [15 minutes]	0,375	0,102	105,69	2	< 0,001
Trip time [between 15 and 30 minutes]	0,197	0,094			
Trip time [30 minutes]	0				
Trajectory [mostly cycling paths]	0,280	0,036	60,82	1	< 0,001
Trajectory [mostly car road]	-0,280				
Weather [good (dry and not windy)]	0,528	0,034	237,15	1	< 0,001
Weather [bad (wet and windy)]	-0,528				
Type [normal e-bike]	0,587	0,058	102,76	1	< 0,001
Type [speed pedelec]	-0,587				
Shower [present]	0,143	0,050	8,17	1	0,004
Shower[absent]	-0,143				
Parking [present *with* option to charge battery]	0,802	0,112	70,86	2	< 0,001
Parking [present *without* option to charge battery]	0,042	0,098			
Parking [absent]	0				
Financial intervention by employer [present]	0,557	0,056	98,71	1	< 0,001
Financial intervention by employer [absent]	-0,557				
No-choice parameter	-0,817	0,098	69,08	1	< 0,001
Hosmer-Lemeshow	27,921			7	< 0,001

The estimation results of the no-choice binomial logit model containing the significant attribute effects are shown in Table 3. The simplifying assumption of uncorrelated parameters, between the attributes is justifiable here. The correlations of the mean parameter estimate between the different attributes are very small. Appendix C shows the correlation matrix of the estimated parameters. All seven attributes are statistically significant at the level of 5%. The effects of all the attributes have a relatively small subject standard deviation. They illustrate a small degree of unobserved preference heterogeneity.

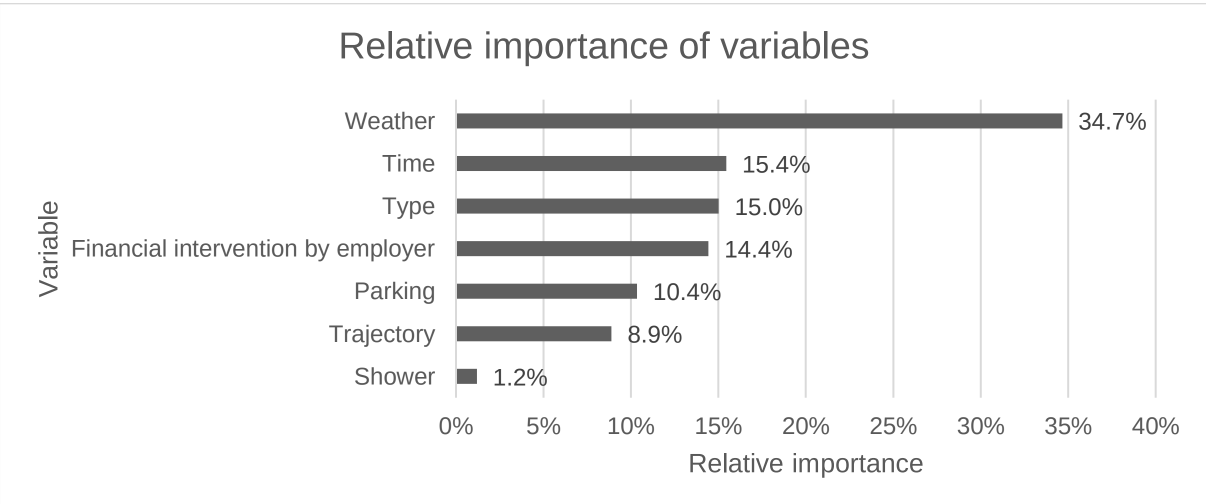


Figure 4. Importance of the Main Effects of the E-bike Journey Attribute

Figure 4 is a bar chart of the relative importance of the different variables. This is calculated by dividing the Wald score of a variable by the sum of Wald scores of all variables The modelling results in Table 3 and Figure 4 show that commute trips were highly sensitive to weather conditions. Adverse weather had a strong negative effect on the likelihood of using an e-bike to go to work, similar to van den Bergh et al., 2018. The presence of showers at the workplace clearly had the lowest impact. The effect of work-related factors was somewhat limited - they accounted for only 26.0% (14.4% + 10.4% + 1.2%) of the combined importance of the investigated variables, which though relatively insignificant, did play a part in the commuters' decisions to e-bike to work. As Table 3 shows, the availability of these attributes (showers, parking, and financial enticements) had a positive effect (similar to e.g., Vanoutrive et al., 2009). We also see that an adjusted trajectory for cyclists created a positive environment for e-bikes. Although this impact was limited, it suggests that investment in high quality cycling paths pays off. This is in line with previous findings (e.g., Goldmann & Wessel, 2020; van den Bergh et al., 2018).

When looking at the type of e-bike, we found a preference for normal e-bikes. This may have been due to the unsafe image of speed pedelecs. Only 5.7% of the 144 respondents expressed a desire to own one (Table 1). This seemed to confirm that a speed pedelec and a normal e-bike are two separate types of bicycle, and should be approached accordingly; the difference in price and speed means that they are very different. Policy actions to improve their modal share of commuting journeys need to be chosen carefully. The effect of trip time was straightforward, though important: shorter trip times were preferred over longer times. Therefore, the potential for greater use of e-bikes lies in shorter range commute trips. Figures 5, 6, and 7 display the effect of gender, e-bike ownership, and age, respectively, on the same seven variables (see Appendix A).

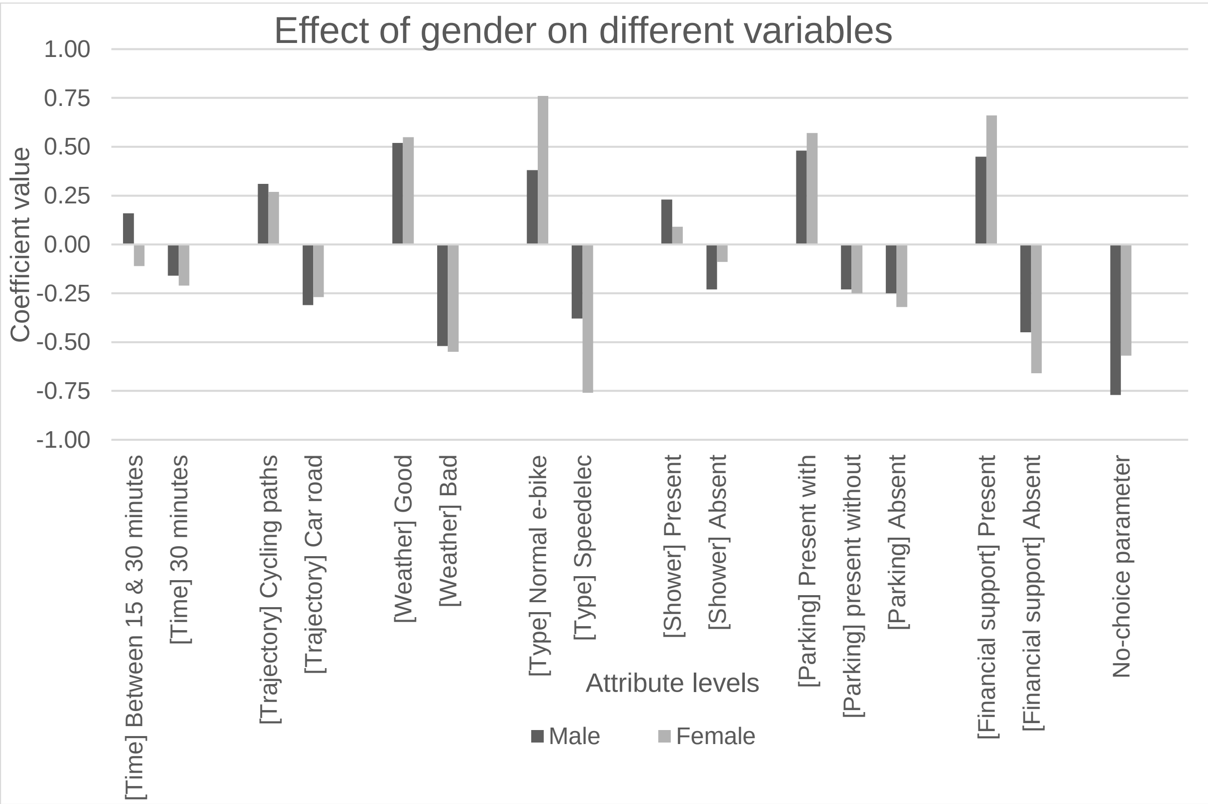


Figure 5. Effect of Gender on Different Variables

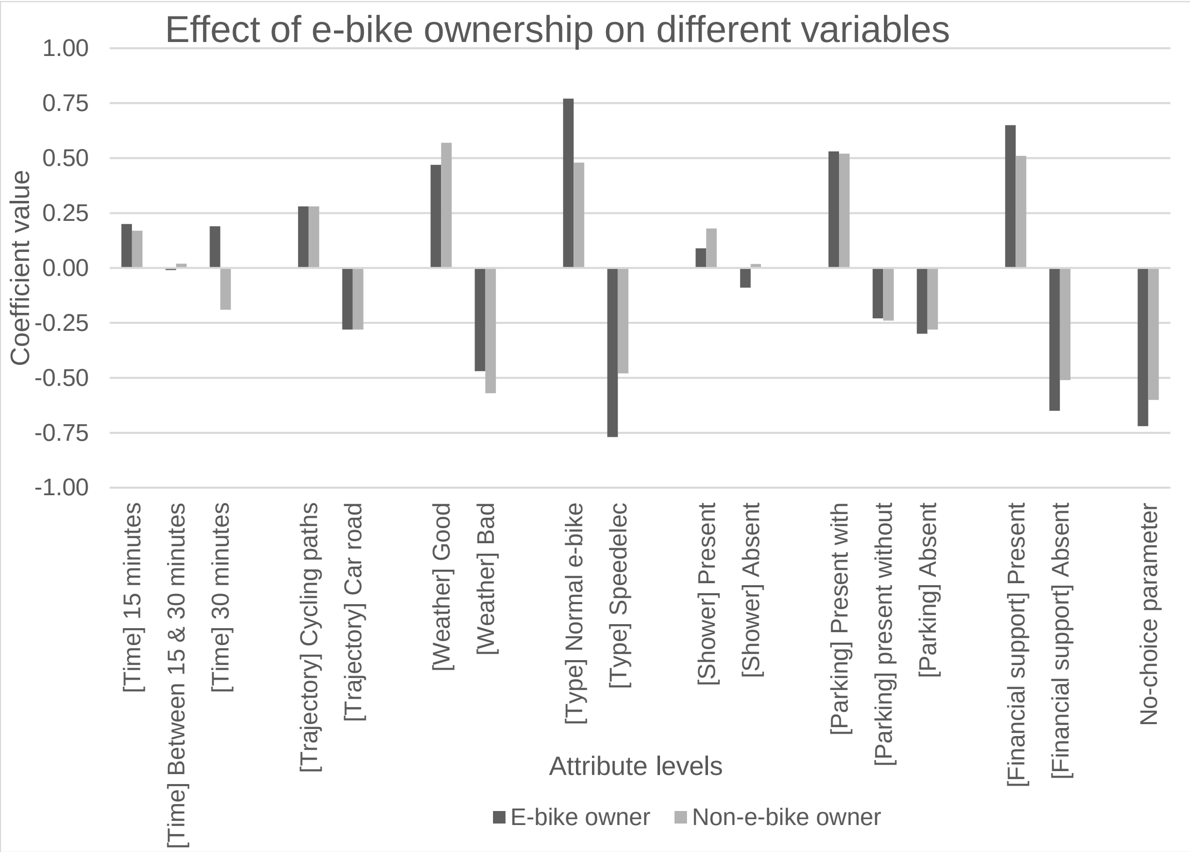


Figure 6. *Effect of E-bike Ownership on Different Variables*

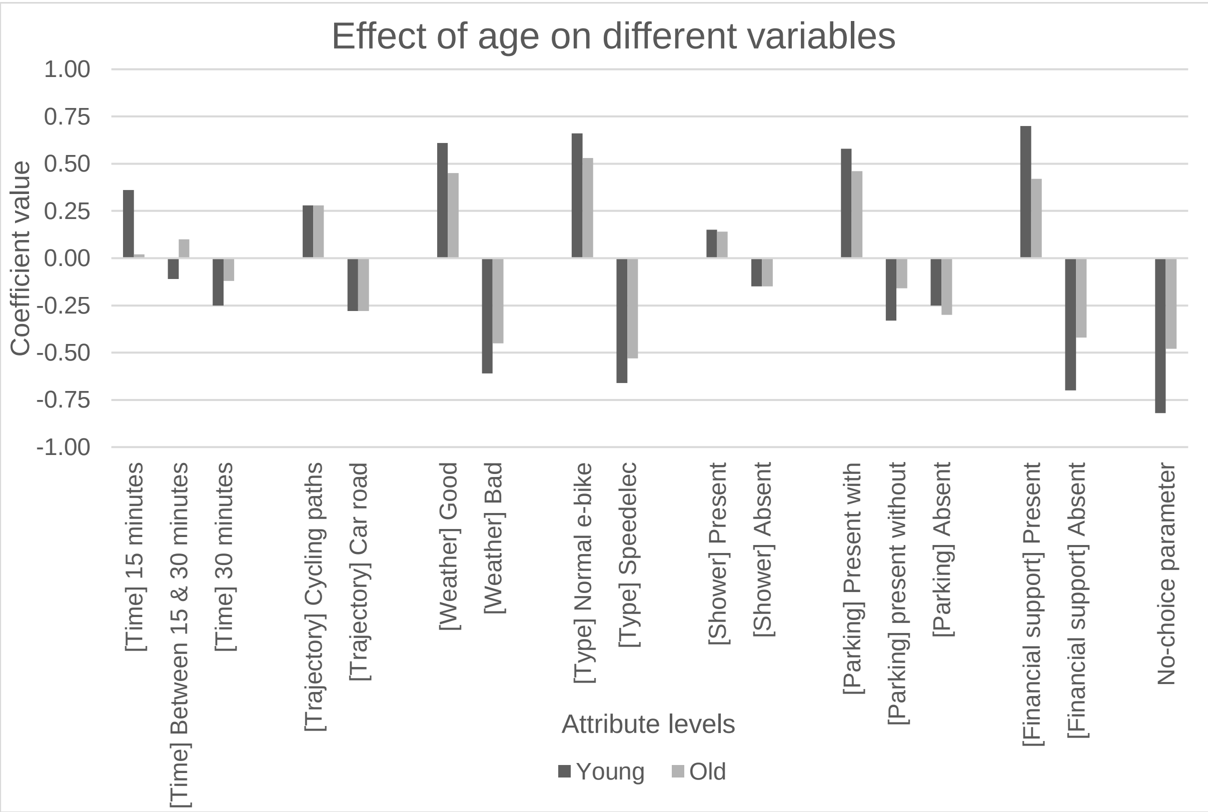


Figure 7. *Effect of Age on Different Variables*

Figures 5, 6, and 7 show that minor differences existed between each of the two groups. Using a Wald chi square statistic, we determined the differences that were truly significant (Peruzzi et al., 2015). For the differences based on gender (Figure 5), these were the variables "time," "type of e-bike," and the "no choice" option. Female respondents evaluated a normal e-bike very positively and speed pedelecs very negatively. For male respondents the difference was more moderate, though they also evaluated normal e-bike positively and speed pedelecs negatively. These results contrast with the findings of Nematchoua et al. (2020), who found no significant differences between male and female users with regard to speed. The difference in the no choice option led us to conclude that the likelihood of e-cycling is higher among female respondents. The none-of-these alternative is slightly chosen more in our study by male than by female respondents. These findings were in line with Cherry and Cervero (2007). Wooliscroft and Ganglmair-Wooliscroft (2014) found no gender effect. Campbell et al. (2016) concluded that the likelihood of e-cycling decreased amongst females. There might be a contextual effect in the case of the latter study, since it was based on Chinese cities using shared e-bikes.

When focusing on the difference between e-bike owners and non e-bike owners (Figure 6), only the variable "type of e-bike" was significant. This can be related to the type of e-bike the owner possessed. The survey did not contain a question on the type of e-bike, though it seemed likely that the majority owned a normal e-bike; hence, the "usual" option was chosen more. These findings were similar to Simsekoglu and Klöckner (2019) and Zijlstra (2016).

The significant differences between young and old respondents (Figure 7) were "trip time," "weather conditions," "financial intervention by the employer," and the no-choice option (See Appendix A for a full analysis and results). The preferences of both groups were rather similar, and always in the same direction. However, the younger age group had a more pronounced preference than the older age group. The "none-of-these" alternative had a higher likelihood of being chosen by the young age group. Therefore, e-cycling was more an older preference. Campbell et al. (2016) and Cherry and Cervero (2007) also found that the older the respondent, the higher the likelihood of them being e-cyclists.

Our findings suggest that the likelihood of using an e-bike for commuting depends on a number of specific factors that are in line with similar studies on cycling in general. This means that getting people to make a modal shift to e-bikes or regular bikes will require similar policy measures. Investment in e-bikes will generally benefit regular cyclists and vice-versa. The only potential difference are related to facilities at the workplace, for e-bike users absence of charging infrastructure can be a limitation while for regular cyclists this is not a problem. We also foresee a difference with regard to shower facilities. For e-bike users, this will be less of a barrier than for the group of regular bicycle commuters who travel longer distances and have more.

5. Conclusion

We investigated how multiple contextual elements influenced the likelihood of using an e-bike to go work. Since the combination of exponentially rising e-bike sales figures and a large amount of people who live in e-bike range from their work mean that this mode of transport has great potential, research on the topic is useful. The data for the present study were collected using an online SharePoint survey amongst working adults in Flanders (Belgium). E-bike ownership was not a requirement. Respondents had to choose what transport mode they preferred. Each CBC question/choice-set presented two e-bike commute alternatives and a no-choice alternative. These differed in terms of trip time, trajectory, weather conditions, type of e-bike, and three work related variables (shower, secure parking, and financial intervention by the employer).

The dominant influencing factor in e-bike commuting was the weather. Bad weather had a substantial negative effect on the likelihood of choosing to go to work on an e-bike. This is in keeping with the general bicycle literature and the limited literature on e-bikes (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). Trajectory and shower facilities at the workplace were the least important variables. As was expected, the presence of most variables (i.e., cycling lanes, secure parking, showers, and financial intervention) had a positive effect. The absence of such facilities had a negative impact on the likelihood of using an e-bike for commuting. Respondents preferred normal e-bikes over speed pedelecs, and shorter trip times were preferred in commuting related conditions.

The recent COVID-19 pandemic and lockdown measures have disrupted people's mobility; moreover, it has given policymakers the opportunity to rethink mobility and support alternative modes of transport, such as e-bikes (Van Wee and Witlox, 2021). Our findings suggest several policy recommendations. First, we find that investments in high-quality cycling infrastructure and mileage allowances both have a positive effect on the likelihood that people will use the e-bike. Similar policy recommendations can be made with respect to the presence of e-bike facilities at workplaces (e.g. shower and secured parking). Moreover, an increase in e-bike use will also lead to an increase in overall bicycle use (Fyhri & Sundfør, 2020). However, it is important to realise that policy makers cannot directly solve all disadvantages of e-bike use. The strong negative effect of bad weather, for example, is such that e-bikes are not always an option. Nevertheless, policymakers can counter bad weather by investing in high-quality cycling infrastructure and thus creating a so-called 'cycling culture' (e.g. Goldmann & Wessel, 2020). The preference of (potential) e-bike users is usually for regular e-bikes. This calls into question the focus of some policymakers on speed pedelecs. To make (e-)cycling a truly sustainable and socially inclusive mode of transport in the broad sense, more is needed than constructing cycling highways and providing tax incentives.

It is important to note here that the effects of the parameters that have been discussed differ slightly between different socio-demographic groups. Younger respondents had more pronounced preferences than older ones, but they were all in the same direction. E-bike owners preferred a normal e-bike over a speed pedelec more than non e-bike owners would. This was presumably related to the unsafe image of these specific pedelecs and the fact that the majority of e-bike owners owned a normal e-bike. Furthermore, female respondents showed a higher likelihood of using an e-bike than male respondents. Other significant differences between female and male respondents were trip times and types of e-bike.

Future studies should examine how these and other factors play a role in other contexts. Other elements, for example distance, safety, effort, time gain, environmental impact, and price might also influence e-bike use. A larger, more diverse sample of commuters could lead to further insights. In terms of methodology, several improvements are possible, e.g. using pivot designs that are customised to each respondent characteristics and using a mixed logit model instead of a no-choice binary logit model to estimate the coefficients. Further, we could use latent class analysis to identify groups of respondents with similar preferences.

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Appendices

Appendix A: The Effect of Different Socio-demographic Variables on Influencing Factors

Table 4. Effect of gender on variables

	B male	**SE**	**B female**	**SE**	**Wald Chi square stat.**	**Sig. p-values**
Intercept	-0,96	0,055	-0,74	0,04	10,464864	p<0,05
Time						
• **15 minutes**	0	0,11	0,32	0,09	5,0693069	p<0,05
• **Between 15 and**	0,16		-0,11			
30 minutes	-0,16	0,06	-0,21	0,07	0,2212389	
• **30 minutes**						
Trajectory						
• **mostly cycling**	0,31	0,06	0,27	0,05	0,2622950	
paths	-0,31		-0,27			
• **mostly car road**						
Weather						
• **Good (dry and**	0,52	0,05	0,55	0,05	0,18	
not windy)	-0,52		-0,55			
• **Bad (wet and windy)**						
Type						
• **Normal e-bike**	0,38	0,08	0,76	0,08	11,28125	p<0,05
• **Speed pedelec**	-0,38		-0,76			
Shower						
• **Present**	0,23	0,08	0,09	0,07	1,73451327	
• **Absent**	-0,23		-0,09			
Parking						
• **Present *with***	0,48	0,1	0,57	0,08	0,49390243	
option to charge						
battery	-0,23	0,08	-0,25	0,07	0,03539823	
• **present *without***						
option to charge	-0,25		-0,32			
battery						
• **Parking: absent**						
Financial intervention by employer						
• **Present**	0,45	0,08	0,66	0,08	3,4453125	
• **Absent**	-0,45		-0,66			
No-choice parameter	-0,77	0,06	-0,57	0,04	7,6923076	P<0,05

Table 5. Effect of e-bike ownership on variables

	B e-bike	SE	B non e-bike	SE	Wald Chi square stat.	Significant p-values
Intercept	-0,82	0,05	-0,82	0,04	0	
Time						
• **15 minutes**	0,2	0,11	0,17	0,09	0,044554	
• **Between 15 and 30 minutes**	-0,01		0,02			
• **30 minutes**	0,19	0,08	-0,19	0,06	0	
Trajectory						
• **mostly cycling paths**	0,28	0,06	0,28	0,05	0	
• **mostly car road**	-0,28		-0,28			
Weather						
• **Good (dry and not windy)**	0,47	0,05	0,57	0,04	2,439024	
• **Bad (wet and windy)**	-0,47		0,57			
Type						
• **Normal e-bike**	0,77	0,1	0,48	0,07	5,644295	p<0,05
• **Speed pedelec**	-0,77		-0,48			
Shower						
• **Present**	0,09	0,08	0,18	0,06	0,81	
• **Absent**	-0,09		0,018			
Parking						
• **Present *with* option to charge battery**	0,53	0,1	0,52	0,08	0,006097	
• **present *without* option to charge battery**	-0,23	0,08	-0,24	0,07	0,008849	
• **Absent**	-0,3		-0,28			
Financial intervention by employer						
• **Present**	0,65	0,09	0,51	0,07	1,50769	
• **Absent**	-0,65		-0,51			
No-choice parameter	-0,72	0,05	-0,6	0,04	3,51219	

Table 6. Effect of age on variables

	B young	SE	B old	SE	Wald Chi square stat.	Significant p-values
Intercept	-0,86	0,05	-0,79	0,05	0,98	
Time						
• **15 minutes**	0,36	0,1	0,02	0,01	5,78	p<0,05
• **Between 15 and 30**	-0,11		0,1			
minutes	-0,25	0,07	-0,12	0,07	1,7244897	
• **30 minutes**						
Trajectory						
• **mostly cycling**	0,28	0,05	0,28	0,05	0	
paths	-0,28		-0,28			
• **mostly car road**						
Weather						
• **Good (dry and not**	0,61	0,05	0,45	0,05	5,12	p<0,05
windy)	-0,61		-0,45			
• **Bad (wet and windy)**						
Type						
• **Normal e-bike**	0,66	0,09	0,53	0,08	1,1655172	
• **Speed pedelec**	-0,66		-0,53			
Shower						
• **Present**	0,15	0,07	0,14	0,07	0,0102040	
• **Absent**	-0,15		-0,15			
Parking						
• **Present *with* option to charge**	0,58	0,09	0,46	0,09	0,8888888	
battery	-0,33	0,08	-0,16	0,08	2,2578125	
• **present *without***						
option to charge	-0,25		-0,3			
battery						
• **Parking: absent**						
Financial intervention by employer						
• **Present**	0,7	0,08	0,42	0,08	6,125	p<0,05
• **Absent**	-0,7		-0,42			
No-choice parameter	-0,82	0,05	-0,48	0,05	23,12	p<0,05

Appendix B: Design CBC

The design of the CBC includes 16 choice sets with two real-choice partial profiles of e-bike journeys, shown in Table 7, and a no-choice option for another transport mode (e.g., car, public transport). We generated this fractional factorial design algorithm with a no-choice option using the Fedorov algorithm. Table 8 presents the combination of the sixteen different profiles in sixteen questions. Each profile is once Profile 1 and once Profile 2 (e.g., profile 20 is profile 1 in question 12 and Profile 2 in question 5.

Table 7. Fractional design

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

Table 8. 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**
9	**39**	**160**
10	**203**	**77**
11	**85**	**119**
12	**20**	**223**
13	**77**	**162**
14	**273**	**96**
15	**162**	**201**
16	**215**	**62**

Appendix C: Correlation Matrix

Table 9 presents the correlations of mean parameter estimates. These are mostly small to very small. Only between financial intervention by the employer and type of e-bike there is a relatively large correlation. This confirms our previous simplifying assumption that our parameters are mostly uncorrelated.

Table 9. Correlation matrix of the parameter estimates of the binomial logit model

		1	2	3	4	5	6	7
1	Trip time [15 minutes]	1	-0,126	-0,126	0,086	0,086	0,069	0,069
2	Trajectory [mostly cycling paths]		1	-0,016	0,098	-0,358	0,022	0,126
3	Weather [good (dry and not windy)]			1	-0,163	-0,098	-0,178	0,126
4	Type [normal e-bike]				1	-0,200	0,390	-0,516
5	Shower [present]					1	-0,121	-0,258
6	Parking [present *with* possibility to load battery]						1	-0,128
7	Financial intervention by employer [present]							1