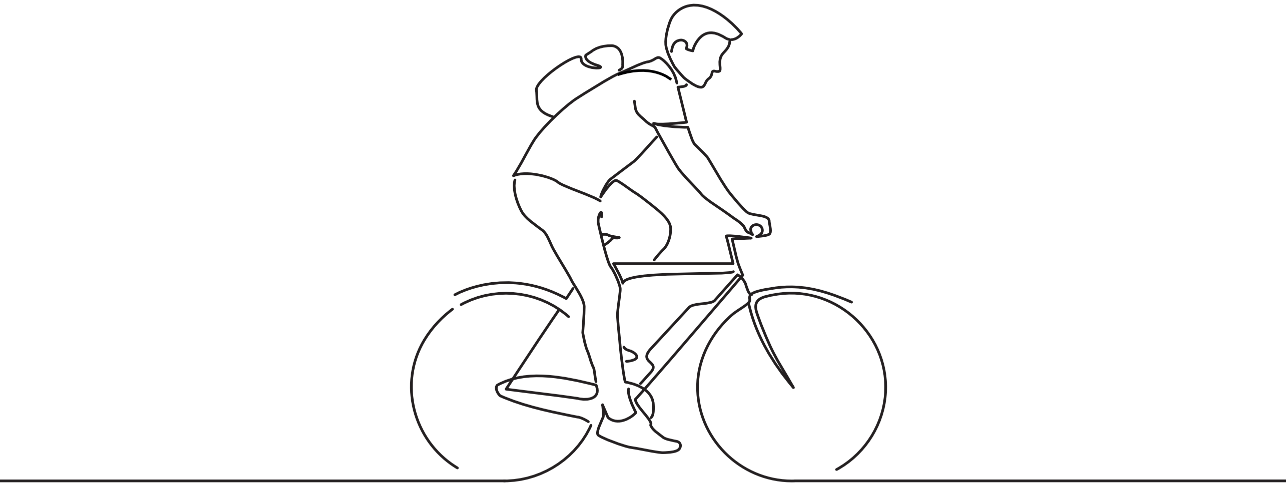
E-cycling to work

Incentivizing behavioral change and the road to well-being



Joost de Kruijf

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Elektrisch fietsen naar het werk
Stimuleren van gedragsverandering en de weg naar welzijn

(met een samenvatting in het Nederlands)

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Willem Johan de Kruijf

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As in many journeys, this process took place in different stages. After completing my master's thesis at Utrecht University, the first seed was planted to start a PhD project. While working as a consultant in traffic and transport modelling at the time, it took me some of years before the opportunity became viable. I owe a great deal of gratitude to Breda University of Applied Sciences in person of Leo Kemps for giving me the time and space to develop the research topic. Because of my own interest in the topic of (e-)cycling and the increasing political attention on the topic, I decided to focus on data-driven behavioral change towards e-cycling. At that time, focus on data-driven cycling policy enhancement was limited. I would therefore especially like to thank Irene Cortenbach from the Metropolitan Region Eindhoven for financially supporting the research project in its early stages.

After initialization of the topic, the first stage of the journey started. All PhD candidates can confirm that we are pushed from pillar to post and back several times during this stage. Having a geographer and a civil engineer as supervisors, the research set-up led to robust yet interesting discussions. I would therefore like to express a great deal of thankfulness to Dr. Martin Dijst for the possibility to start my PhD at Utrecht University and his useful advice in helping me understand several important concepts in behavioral change. Although the concept of Basic Human Values (BHV) was not incorporated in this book, I would like to thank Professor Dr. Schwarz and my friend Liesbeth Baks for the support in translating the BHV concept into the longitudinal surveys. I also wish to express my gratitude to the cycling policy team of the Province of Noord-Brabant for offering me the opportunity to conduct my research within the B-Riders program and for all their support, patience, and trust in my work. Despite some strong discussions in the development phase of B-Riders, the result was worthwhile as award-winning behavioral change program. I believe together with the Brabantstad partners we achieved many cycling-related policy enhancements and innovations over the last decade because of the teamwork.

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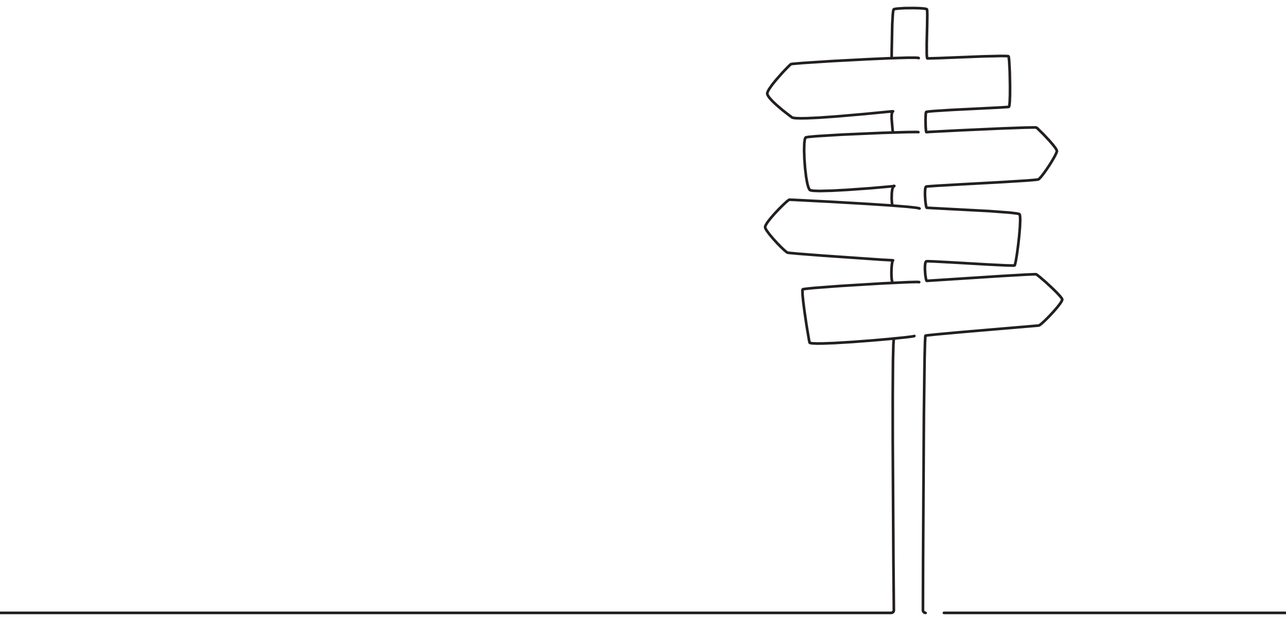
CHAPTER 1

Introduction



1.1 Introduction

Many cities and regions develop plans toward establishing more sustainable and inclusive mobility systems that are independent of the present day car-dependent lifestyles. To achieve more sustainable forms of mobility, policymakers stimulate a change in behavior toward the use of travel modes, such as walking and cycling (Commission of the European Communities, 2007), which produce less noise, pollution, and greenhouse gasses. This transition is of particular importance since these active transport modes not only reduce greenhouse gas emissions but also have positive effects on mental and physical health that result from an increase in physical activity (Sugiyama et al., 2008; Akar and Clifton, 2009; Badland and Schofield, 2008). Despite the advantages of these active transport modes, it should be noted that such modes substantially differ between countries. In general, public engagement in cycling is often low (Cavill et al., 2019; Strain et al., 2016; Buehler and Pucher, 2012). In countries in which cars are dominant (such as the United States [US]), utilitarian cycling is often still considered a fringe activity and suffers from a renegade image (Pucher et al., 2011; Moudon et al., 2005). Research has shown that 12% of people in Europe across 28 member states cycle every day (European Commission, 2013). The proportion of non-motorized transport in total daily travel in major European cities varies largely and ranged from 5% in Paris (France), 14% in Helsinki (Finland), 49% in Copenhagen (Denmark) in 2019 (ECF, 2019), and 42% in Utrecht (the Netherlands) in 2020 (CBS, 2023). Next to the varying cycling proportions, the distance traveled by bicycle is rather limited with only 3% of the total distance traveled considered active travel (walking and cycling) in England (Department for Transport, 2018). In the US, less than 1% of the population uses the bicycle to commute (League of American Bicyclists, 2019).

Extensive research on active travel and specifically the use of the conventional bicycle (Heinen et al., 2010; Heinen and Handy, 2012; De Geus et al., 2013; Cauwenberg et al., 2018; Gatersleben and Appleton, 2007; Vandenbulcke et al., 2009) identified determinants for cycling, more specifically the use of a bike to commute to work. Apart from cultural and societal factors, personal and household characteristics, topography, distances, and time limitations are other important factors influencing cycling behavior. Although cycling can be regarded as an option for many commuters for mid-range distances (< 15 km), a considerable number of these commuters choose to use other modes of transportation. Previous research has shown that people living close (< 5 km) to work are significantly more likely to use their bicycle compared to people with a longer commute (Dickinson et al., 2003; Kingham et al., 2001; Krizek, 2010). The unattractiveness of cycling for longer distances is related to physical effort and limited speed and range. With the introduction of the bicycle-style electric bike ([e-bike][1] Dill and Rose, 2012; MacArthur et al., 2014), new opportunities

[1] Electrically power assisted cycles - EPAC Bicycles (EN 15194:2017)
The bicycle-style e-bike or electrically power assisted bicycle has a maximum continuous rated power of 0,25 kW of which the output is progressively reduced and finally cut off at a speed of 25 km/h, or sooner, if the cyclist stops pedaling and is intended for use on public roads.

for a change toward sustainable travel behaviors has arisen given the lower required physical effort and greater speeds; therefore the ranges these e-bikes can travel is greater compared to conventional bicycles.

The introduction of commercially available e-bikes took place in Japan in the early 1980s (Rose, 2012), but the market attractiveness was limited until the early 2000s (Jamerson & Benjamin, 2013) due to technological and cost factors. Since the beginning of this century, the cycling range and speeds of e-bikes have been extended because of improved battery and motor technology. Also, economies of scale improvements have resulted in more affordable e-bikes (Jamerson & Benjamin, 2013). During the first period after the introduction of these e-bikes, they were regarded as mobility products for elderly people (Fishman and Cherry, 2016). As the technology developed and its appearance modernized, the e-bike became more popular among other age cohorts. In the Netherlands, more than half of the new bicycles (57%) sold in 2022 were e-bikes (BOVAG, 2022).

Over the last decade, the e-bike has attracted a considerable amount of research-related attention (Bourne, 2020; Cavill et al., 2019; Sundfør and Fyhri, 2017; Plazier et al., 2017; Dill and Rose, 2012; Fishman and Cherry, 2016; MacArthur et al., 2014; Popovich et al., 2014; Jones et al., 2016) as an alternative to car-oriented lifestyles. In areas in which public transport is dominant, such as in many Chinese cities with less established cycling cultures, the shift to e-bikes came at the cost of public transport usage (Cherry and Cervero, 2007; Kroesen, 2017). In the North American and Australian context in which the car is dominant, using an e-bike instead of a car has proven to be a key motivator for purchasing an e-bike although on a small scale (Johnson and Rose, 2013; MacArthur et al., 2014; Popovich et al., 2014). These studies suggest that the number of car trips is reduced by e-bike ownership. The advantage of these bike's higher range, easier acceleration, higher speed, and easier ascent of hills compared to the conventional bicycle results in longer trips being taken using this bicycle for a greater variety of purposes (Langford et al., 2013). In the Northwest European context, research shows that the percentage of cycling trips almost doubled when cyclists were provided with an e-bike (Fyhri and Fearnley, 2015). Next, in terms of the intended modal shift from car to e-bike use in daily commuting, corresponding change from use of the conventional bicycle to use of the e-bike has also occurred. Since the benefits of the less physical activity required for e-cycling compared to the conventional bicycle exists, the added value of positive health effects might therefore be questioned. Compared to cars, e-bikes are eighteen times more energy efficient (Shreya, 2010). The physical activity is lower while riding an e-bike than during conventional cycling but markedly higher than traveling by car (Simons et al., 2009; Sundfør and Fyhri, 2017). Although these studies provide insights into the substitution of trips and adoption rate of e-bike use, limited insights still exist into factors influencing individual e-bike use (Plazier et al., 2017; Sun et al., 2020; Sundfør and Fyhri, 2017). Based on data from a general mobility study, a Dutch study investigated the substitution of travel modes related to e-bike ownership (Kroesen, 2017). This study suggests that e-bike ownership results in a decrease of ownership and use of the conventional bicycle rather than a reduction in ownership and use of a car and use of public transport.

While the body of knowledge about the uptake and use of the e-bike is gradually developing, one aspect that has received limited attention is the use of e-bikes over a longer time frame (Plazier, et al., 2017; Sun et al., 2020). Since most studies are based on cross-sectional studies, limited insight is available into how the use of e-bike is sustained over a longer period, what factors influence the adherence to e-biking, and whether e-biking has effects on well-being and health over a longer period. Such insights are important since the e-bike is (despite the current trend in the Netherlands) in many contexts is a relatively new travel mode (Fishman and Cherry, 2016) with which many will be unfamiliar. As a consequence, switching to such a new mode can be considered a process of learning and gaining experience, the dynamics of which are not well known. Yet, to successfully introduce e-bikes as an alternative to car travel, such knowledge would be important. In addition, the introduction of e-bikes often occurs in the context of stimulation programs. These stimulation programs can be divided into programs focusing on getting acquainted with the e-bike and programs that stimulate e-bike use, in which participants receive feedback on their e-bike use in the form of financial and non-financial feedback, such as information provision and social approvement. Also, to develop successful e-bike stimulation programs, insight into the longer-term dynamics in behavior and experience of e-biking are important. Hence, additional research is needed for better understanding of how a lasting behavioral change towards e-cycling can be brought about to develop effective policies for substituting a car for an e-bike.

This thesis aims to contribute to adding information to the above-described knowledge gap by investigating the driving forces and barriers of the structural shift from car to e-bike and its implications for well-being. Driving forces and barriers include both internal and psychological factors, which influence travelers' intention to change their behavior and then actually change it, in addition to external factors, such as distance, weather, and/or built environment factors. In addition, given the focus on longer-term outcomes, the effects of a shift to e-biking on travelers' well-being is important, not only since well-being outcomes are relevant societal outcomes but also because well-being has been found to be a determinant of continuing new behaviors (Oliver, 1980). Accordingly, the goal of this study is to provide insight in large-scale long-term behavioral change towards commute e-cycling in the Dutch context, considering both internal and external factors and taking well-being effects into account.

1.2 Background

Stimulating e-cycling: behavioral mechanisms

To stimulate e-cycling, Dutch policy makers have focused both on physical measures, such as developing high-quality cycling routes and parking infrastructure, and on financial and organizational measures, such as stimulating an interest in cycling by setting up incentive programs, subvention regulations with employers, and tax regulations. Having a safe and comfortable bicycle path network is regarded as a prerequisite for cycling. Over the last couple of years, a strong increase in academic research linking bicycle infrastructure to cycling levels has developed. Despite this substantial increase in the number of studies in recent years, important gaps in the literature remain (Buehler and Dill, 2016). Although various studies have addressed how individual characteristics, such as width, pavement, and illumination, of a cycle path network affect cycling levels, a scarcity of scientific studies examining the effect of the overall network characteristics on cycling behavior exists (such as the role of missing links, connectivity, and cohesion). From an individual user's perspective, studies often rely on samples of volunteers or avid cyclists (Buehler and Dill, 2016). Such self-selection distorts the generalizability of quantitative analysis, and it also means that certain target groups (such as lower income and minority groups, and young children) that would disproportionally benefit from cycling more (Martens, 2013) from both equity and health perspectives are likely to be underrepresented. Finally, improving the policy effectiveness of e-cycling promotion does not only require better knowledge of the impact of network features, design elements, and/or specific policy interventions. It also requires insight into how they can successfully contribute to scaling e-bike use. Scaling e-bike use means that more people need to start cycling, which also requires insight into the underlying behavioral change process over time.

Regarding the shift to e-cycling as a more general behavioral change, a large body of literature is already available to help conceptualize this shift (see Cairns et al., 2017; Fujii and Taniguchi, 2006; Gärling and Fujii, 2009)). Literature studies suggest that interventions aimed at behavioral change can be classified as three main pillars: (1) money, (2) power, and (3) words (Gärling and Fujii, 2009). The first pillar not only refers to money in the strictest sense but also to factors such as physical travel circumstances (such as that affected by improved infrastructure) and travel time. Power refers to physical barriers in addition to political regulations that force people to behave in a desired way. Finally, "words" refer to various types of information, communication, and education that may change people's behavior. Information can, for instance, be provided about positive or negative health effects or environmental impacts, or it can provide feedback to individuals about their specific behaviors. Another classification of measures aimed at behavioral change is the distinction between pull and push measures (Steg, 2003). In the case of the shift from car to e-bike, push measures imply a decrease in benefits associated with car use, whereas pull measures refer to the increase in the benefits of using an e-bike. Stimulation programs of e-cycling can be regarded as a typical pull measure.

Irrespective of the type of intervention, a behavioral change can be described in terms of individuals' decision-making processes based on psychological theories. The often used Theory of Planned Behaviour ([TPB] Ajzen, 1991) proposes that behavior (including that related to travel) is driven by personal attituded toward the intended behavior, subjective norms or influence of people important to a person, and perceived behavioral control as evaluation of being capable of conducting the intended behavior. This set of belief-related variables determines the intention to engage in certain intended behavior (or not). The TPB has been used in the domain of residential relocation, for example, change in favor of public transport, and health as a theoretical framework to understand behavioral change (see Bamberg, 2006; Hunecke et al., 2001; Hardeman et al., 2010). Although the TPB is a relevant framework for understanding behavioral change, more frameworks that provide starting points for behavioral interventions are available.

Next to the belief-related variables from the TPB, habits play an important role in generating behavior (see James, 1981; Triandis, 1977; Watson, 1913). Habits are formed through repetition of behavior in specific contexts (Lally et al., 2010). Although habits are known to underpin behavior for many years (see James, 1981; Watson, 1913), the interest in habits involved in health behaviors has revived in general (e.g., Gardner et al., 2011; Lally & Gardner, 2013; van t'Riet, et al., 2011) and particularly related physical activity (Rhodes & de Bruijn, 2010). Habit theory contains important implications for behavioral change interventions. Pursuing positive behaviors should maintain the impact of the intervention over time since old or habitual behaviors might be resistant to change (Rothman et al., 2009; Verplanken & Wood, 2006).

Theories of affect and well-being (Russell, 2003) and satisfaction (Oliver, 1980) are increasingly applied to transportation research (Olsson et al., 2013; Ettema et al., 2011). In short, these theories assume that the act of traveling affects travelers' well-being in terms of both cognitive and affective (emotional) components (Abou-Zeid and Ben-Akiva, 2012; Ettema et al., 2011; Morris and Guerra, 2015). To achieve a behavioral change toward e-cycling, it is important to understand the affective evaluation of car use. In general, private cars invoke a positive affective state due to easy access to out-of-home activities (Bergstad et al., 2012), privacy and security (Gatersleben et al., 2014) and also non-instrumental factors, such as independence, joy, freedom, and car travel as an enjoyable activity in itself (Gatersleben and Appleton, 2007). In contrast to the positive elements to car driving, commuter trips in congested traffic cause residual stress in the workplace in which some car drivers experience high levels of stress. A potentially positive element related to behavioral change toward e-bikes is the fact that satisfaction with active travel has been consistently found to be higher than car use and public transport (Gatersleben and Uzzell, 2007; Martin et al., 2014; Olsson et al., 2013; St-Louis et al., 2014; De Vos et al., 2015). The highest level of satisfaction involves active travel; however, it is likely that personal and environmental factors moderate the level of satisfaction with these modes. When the natural environment is reviewed, hilliness and landscape and weather, seasons, and climate are mentioned. For the constructed environment, factors, such as urban form (implications for trip distances) network layout, quality, and safety of infrastructure and the facilities at the destination affect cycling (Heinen et al., 2010). With regard to the built environment, the duration of the trip by slow modes has a negative impact on travel satisfaction (St-Louis et al., 2014), which is most likely due to fatigue-related effects. A more positive level of satisfaction with travel is likely to contribute to behavioral change.

Next to address the belief-related variables, such as attitude, subjective norms, and perceived behavioral control for the TPB, the Extended Model of Goal-directed behavior (EMGB) specifies habit and goal-related variables, such as goal perceived feasibility, goal desire, and goal anticipated emotions as having an influence on intentions and thereby behavioral change. These anticipated emotions confirm the relevance of affect related to current behavior (Perugini and Conner, 2000). This mechanism suggests that negative affect associated with the outcome of a choice (based on previous experiences) might lead to an increase in the likelihood of changing one's behavior. In marketing studies (Oliver, 1980), satisfaction with a product or service may influence the intention to consume the product a second time.

In addition to the above theories on behavioral intention, research in the public health domain indicates that intention alone is a limited predictor of actual behavioral change ((Faries, 2016; Norton et al., 2015; Grimmer and Woolley, 2014). In particular, in the context of health-related behaviors, such as exercising or giving up smoking, it has been found that intentions are not translated per se into behavior. Hence, if the TPB and EMGB are applied to understand the switch from car use to e-biking based on intentions, it is important to know to what extent intentions to use the e-bike are actually transferred to e-bike use and what factors influence the consistency between intentions and behavior. In addition, in e-bike stimulation programs that usually last for a longer period, it is important to understand how intentions in addition to intention-behavior consistency develop over the course of the program.

Overall, the comprehensive model of behavioral change, based on the above theories, and used for this research is shown in figure 1.1. In this model, the intention to change behavior is affected by both belief-related variables such as the TPB attitude, subjective norms, perceived behavioral control, and goal-related variables, such as goal perceived feasibility, goal desire, and goal anticipated emotions. In addition, habit (Gardner and Rebar, 2019) is considered to influence behavioral intention in addition to behavioral volitions or implementation intentions as suggested by Sniehotta et al. (2005), Reuter et al. (2008), and Wieber et al. (2015).

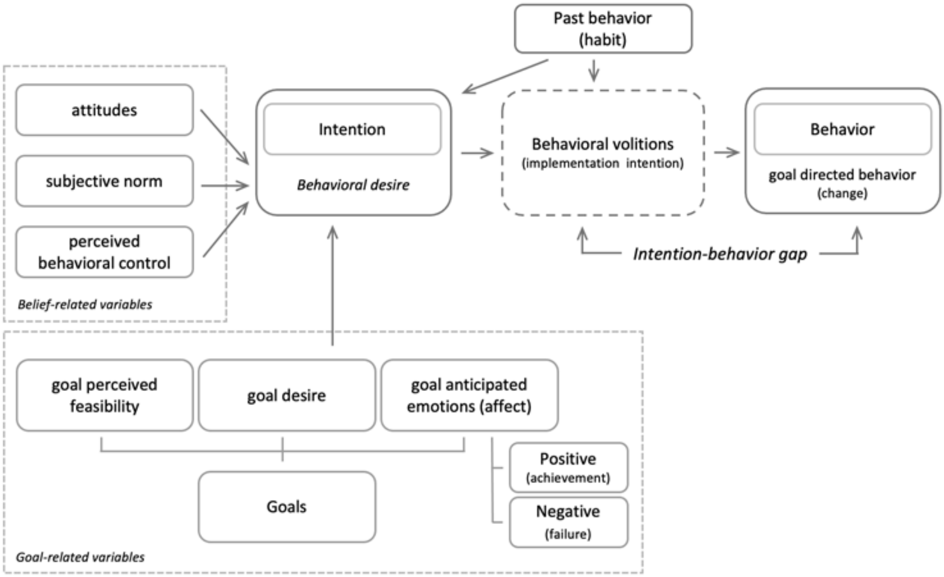


Figure 1.1. Overview of conceptual model

Weather circumstances as dissatisfier to e-cycling

Research by several groups (Heinen et al., 2010; Verplanken and Aarts, 1999) has shown that one of the main determinants that influences the attractiveness of cycling is the natural environment, specifically the weather and climate conditions (Heinen et al., 2010), in which several studies suggest that weather conditions and desire to cycle are closely linked (Corcoran et al., 2014; Nankervis, 1999). The effects of daily weather and climate conditions have been demonstrated for various aspects of travel behavior, including trip generation and choice of mode (Böcker et al., 2013; Creemers et al., 2015; Liu et al., 2015). Regarding active travel, inclement weather conditions have a negative impact (more than for other modes of transport) because of exposure to the elements (Nahal and Mitra, 2018). Compared to non-commuters, commuters appear to be less sensitive to weather changes. Existing studies show that observable weather conditions, such as wind, total precipitation, and air temperature impact cycling. In general, dry, warm and sunny weather positively influences walking and cycling, whereas wet, cold, and windy weather have the opposite effect (Aaheim and Hauge, 2005; Bergström and Magnusson, 2003; Flynn et al., 2012;

Gallop et al., 2011; Nankervis, 1999; Sears et al., 2012; Thomas et al., 2013). Notably, temperature has been found to have a non-linear effect in the sense that very low and very high air temperatures have a negative impact on cycling (Böcker et al., 2019; Miranda-Moreno and Nosal, 2011; Phung and Rose, 2007). Next to the negative impact of rain on cycling at a specific time, this type of condition also affects cycling prior to the actual occurrence of adverse weather conditions due to behavioral anticipation (Zhao et al., 2019). Considerable regional differences in terms of active travel and conventional cycling, specifically in the Dutch, Danish, and Norwegian contexts, were shown by research on the combined effects of weather conditions (Böcker et al., 2019).

Compared to conventional bicycles, e-bikes offer various advantages, in terms of less strenuous required physical effort and greater ranges due to the higher speed (Bourne, 2020; Plazier et al., 2017). As the commuting trip by e-bike requires less time and effort compared to the use of the conventional bicycle, the technical e-bike advantages might also mitigate the negative influence of adverse weather conditions. Less physical effort is related to the need for e-cycling, the sensitivity to strong winds might be less compared to conventional cycling. Another factor which negatively affects cycling is sweating due to physical efforts and high temperatures (Heinen, 2010). It can be assumed that sweating is less of an issue for e-biking given the lower physical effort that is required.

E-bike commuting and well-being

Cycling is widely regarded as an environmentally sustainable alternative travel mode to car travel and is positioned to resolve regional congestion problems related to economic sustainability. At the same time, the bicycle is also contributing to better health due to the physical activity involved (Morris and Guerra, 2015). Apart from these societal benefits of cycling, a shift toward cycling (or e-cycling) may have implications for well-being, which may be regarded as additional societal benefits of policies to promote both conventional and e-cycling. In particular, active travel modes have been shown to lead to higher levels of satisfaction with travel compared to car use and public transport (see Olsson et al., 2013; Mao et al., 2016; St-Louis et al, 2014; De Vos et al., 2015), which carries over in higher levels of life satisfaction (Jacobsson-Bergstad et al., 2010). Next to domains such as family life, professional life, and other aspects, this so-called travel satisfaction can be regarded as satisfaction with a specific life domain and as such, is a concept related to subjective well-being (SWB). Methods to measure Satisfaction with Travel have already been developed and tested (Ettema et al., 2011) in various contexts. Research has shown that travelers develop an evaluation of their travel experiences, which indicates how good and pleasant travel is and how experience can be improved through service and design factors (see Olsson et al., 2013; St-Louis et al, 2014; Jacobsson-Bergstad et al., 2010).

Satisfaction with active travel has been investigated across different geographical contexts and cultures (Olsson et al., 2013; Mao et al., 2016; St-Louis et al., 2014; De Vos et al., 2015), and results indicate that physical activity and exposure to outdoor environments are responsible for higher satisfaction with travel (Ekkekakis et al., 2008). Various studies indicate that the positive effects on mood and well-being (as an elaboration of social sustainability) are not limited to the duration of cycling but also extend to other periods of day and are associated with a higher level of satisfaction with life (Martin et al., 2014; Friman et al., 2017). With regard to regular cycling, the distance range (as a result of lower speed) and physical limitations that apply to part of the population (MacArthur et al., 2014; Popovich et al., 2014) limit the feasibility of cycling. With the introduction of the e-bike those constraints should be mitigated. However, as e-biking is different from conventional cycling in terms of speed, physical effort, and (often) duration, it is unclear if e-biking will lead to a similar level of travel satisfaction. Studying a modal shift to e-cycling and the effects on well-being is important since mood and/or satisfaction associated with new behavior may be an important predictor of adherence to the new behavior as previously mentioned in the paragraph about behavioral mechanisms (Standage and Ryan, 2020). Additionally, it is interesting how satisfaction will develop over a longer period of time as the length of satisfaction development may have implications for long-term adherence.

Regarding the longer term stability of the e-cycling experience and travel satisfaction, the possibility of a hedonic treadmill mechanism should be considered (Diener et al., 2006). This mechanism implies that when circumstances improve, such as those using more attractive modes of transportation, an initial positive effect on people's well-being will occur. While the changed circumstances will be then regarded as the standard after a while and the aspiration level will be raised, the well-being will decrease to its base level. This effect is strengthened over time while individuals pay less attention to the factors that have improved in their circumstances. The hedonic treadmill effect is likely to cause a decrease in the intensity of the emotional impact and the effect on mood and well-being. Therefore, it is questionable as to what extent the shift to e-cycling in daily commuting influences satisfaction with travel over time for participants in a large-scale incentive program.

As satisfaction with e-cycling might influence the structural behavioral change from car to e-bike use in daily commuting, understanding eventual changes in satisfaction with e-cycling over time is important. As e-cycling is an active mode of transport, physical and mental health conditions might be influential in an individual's level of satisfaction with the activity. It is also interesting to understand potential differences in satisfaction levels in terms of travel between people who only use the car to commute and people who have already experienced alternative transportation options. Already, the relationship between conventional cycling and well-being has been explored; thus, the question can be raised to which degree this relationship is also applicable for e-cycling.

1.3 Research aims and questions.

This dissertation aims to deliver insights that contribute to the behavioral change to e-cycling as a sustainable alternative to car-oriented commuting for the short and mid-range distances (<15 to 20 km). It builds upon the current practical as well as academic knowledge about stimulating regular bicycle usage while commuting (Heinen et al., 2010). Some of the known barriers, such as the higher cycling range with less effort, to the use of the regular bike should decrease due to the particular advantages of the e-bike, Over the last decade, extensive research has been done concerning the introduction of the e-bike (Rerat, 2021; Sun et al., 2020; Fishman and Cherry, 2016); however, little attention has been paid to the large-scale behavioral changes after switching from the use of a car use to an e-bike for daily commuting.

The central questions can be asked:
What are the effects of an e-cycling incentive program on short- and longer-term behavioral changes, how can these outcomes be understood from underlying behavioral processes and external factors, and how does the change in behavior lead to changes in travel satisfaction?

Four sub-questions were derived from this general thesis question and are addressed in the individual chapters of this thesis.

1. *What is the effect of the introduction of the e-bike in daily commuting on modal shift and persistence in behavioral change?*

As the e-bike is regarded as a sustainable alternative to car commuting on the short and midrange distances (< 15 km), the first article focuses on the actual behavioral change brought about by an incentive program for e-bike use in daily commuting patterns. Since the Netherlands is known for cycling in daily commuting, the habitual conventional cycling experience might be important. Therefore, the distinction is made between participants with and without habitual conventional cycling experiences while commuting. Research has shown that e-bike ownership substitutes conventional bicycle ownership and is used more than car and public transport (Kroesen, 2017). Based on an incentive program targeted at car commute trip substitution, the longitudinal effects are assessed. Next to the modal shift effects brought about by the incentive program, variables related to e-cycling, such as sociodemographic characteristics, varying cycle distances, and spatial attributes, such as urbanization level, satisfaction with car travel, and number of commuting days per week, are considered to better understand the behavioral changes on an individual level. Using linear regression modeling, effects on the behavioral change toward e-cycling and behavioral persistency were analyzed over a six month period (see figure 1.4).

As the e-cycling incentive program in general is targeted at the shift to e-bikes to reduce car traffic during peak hours, this behavioral change of individuals depends on the intentions formed by participants and the extent to which these are translated into actual behavior. To develop successful e-bike stimulation programs, it is important to determine which factors influence intention-behavior consistency in the context of e-bike adoption. Therefore, the following research question was formulated:

2. *To what extent do participants adjust their behavioral intentions to use the e-bike in daily commuting and changes the intention-behavior gap over time?*

The second article therefore focuses on the changes in intentions, behaviors, and the relationship between them, called the intention-behavior gap. Since many studies either focus on changes in behavioral intentions or behavioral changes with a cross-sectional approach, this study combines both approaches. To better understand behavioral intentions, this study uses belief-related factors, such as personal attitudes, subjective norms, and perceived behavioral control based on the TPB (Ajzen, 1991) and the contribution of different habits (Gardner and Rebar, 2019). In addition, we investigated the effect of goal-directed variables, such as goal-perceived feasibility, goal desire, and goal-anticipated emotions as specified in the EMGB (Perugini, 2000). Relating the belief- and goal-related variables to measurements of actual behavioral changes measured in a longitudinal perspective makes it possible to report on the intention-behavior gap or consistency (see figure 1.1). Based on the longitudinal approach using ordinal regression modeling (see figure 1.4), travel behavior intentions, changes, and consistency can be modeled as a function of sociodemographic characteristics in addition to spatial-, belief-, and goal-related attributes.

Next, to understand the modal shift from car to e-cycling, adjustments in behavioral intentions and changes in intention-behavior consistency, more factors have been proven to influence (conventional) cycling (Heinen et al., 2010). One of the most important environmental factors influencing conventional cycling is the natural environment, specifically climate and weather conditions. The technical advantages of the e-bike might mitigate the negative impacts of the natural environment, making it less sensitive to weather conditions. To address the impact of adverse weather conditions on e-cycling on a day-to-day basis, the next research question is formulated:

3. *To what extent do integrated effects of adverse weather conditions, such as impact of precipitation, temperature, and strong winds affect e-bike use in daily commuting?*

While in previous studies, adverse weather conditions, such as rain, strong winds, and low temperatures have already proven to have a negative impact on cycling, the third empirical article focuses on the weather effects on e-cycling. First, the higher speed of the e-bike reduces travel time to work compared to the conventional bicycle, influencing the time of exposure to precipitation. Second, the increased comfort of the e-bike with its reduced required physical effort compared to the conventional bicycle might influence the negative impact of sweat related to the active form of transport on warm days. Third, on windy days, the electric pedal assist reduces the physical effort needed to cope with (strong) headwinds. By combing continuous commuting behavior measured with global positioning system (GPS)-data, information about weather circumstances from regional weather stations, and socio-demographic information about participants, the impact on e-cycling has been explored using a multivariate regression analysis (see figure 1.4).

Next, in terms of the potential negative impact of weather conditions on e-cycling, it is also important to understand potential positive factors that influence e-cycling. Because cycling is a form of active travel, it affects both physical and mental health in a positive manner. Although the e-bike requires less effort than conventional cycling, the e-bike still contributes to an active lifestyle. Participating in an e-cycling incentive program should accelerate the intended modal shift for which behavioral effects should be long lasting. Because of potential treadmill effects, the positive effects on mental health could be diminished during the program. To address the effect of e-cycling on travel satisfaction and longitudinal consistency, the next research question was formulated:

4. *What effect does the shift from car commuting to e-cycling have on people's travel satisfaction and how does this develop over time?*

The fourth empirical article in this dissertation focuses on the relationship between the modal shift and satisfaction with travel, distinguishing between car-only commuters and people with cycling experience. Based on a longitudinal approach, baseline satisfaction with car commuting and changing satisfaction with e-cycling over time were analyzed considering socio-demographic characteristics, spatial attributes, such as frequency and commute distances, and habitual commute behavior, to better understand the impact of satisfaction with travel on an individual level. Using t-tests and linear regression modeling, effects on the relationship between behavioral change and well-being were analyzed over a six-month period (see figure 1.4).

1.4 Study area, scope, and data

To explore the impact of behavioral changes, behavioral intentions, and intention-behavior consistency, the impact of adverse weather conditions and the satisfaction with travel brought about by the stimulation of e-bike usage in daily commuting, it is important that the study area offers infrastructural, political, cultural, societal, natural, and constructed environmental opportunities (Heinen et al., 2010; Heinen and Handy, 2012) for e-cycling use. The province of Noord-Brabant in the Netherlands (see Figure 1.2) offers such an environment in which a highly political cycling ambition is combined with a flat landscape and a rather dense urban form. Noord-Brabant has a population of approximately 2.5 million inhabitants of which 1.9 million people are living within a range of 15 km from five mid-size cities, each of which are surrounded by several municipalities. Noord-Brabant is known for its high-quality regional bicycling infrastructure and political ambition. Next to the cycle infrastructure investments, the province developed the B-Riders e-cycling incentive program targeted at the potential for e-bike use for the mid-range commute distances for which many trips still were being made by car, causing congestion during the peak hours on the main regional car networks. The B-Riders program within the spatial context of Noord-Brabant provided a unique opportunity to explore the behavioral changes toward e-cycling for which next to the behavioral change itself, the province is continuously looking for cycle policy enhancement to obtain higher cycling shares to meet the regional sustainability objectives.

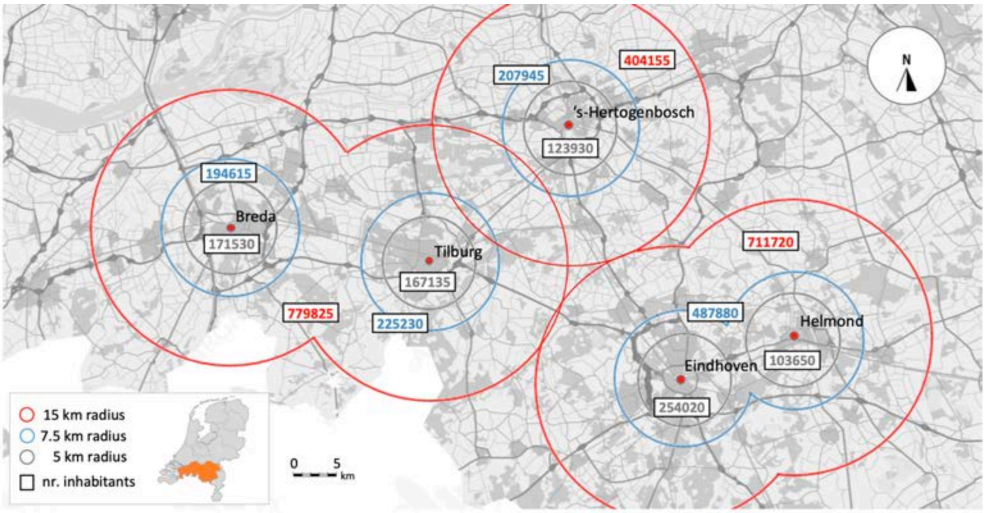


Figure 1.2. Study area

The basis for all research in this thesis originates from a large-scale e-cycling incentive program in Noord-Brabant, called B-Riders, which was initiated in 2013. The B-Riders program is one of the most successful projects in an overarching national program (Beter Benutten) to reduce peak-hour car congestion by substituting e-cycling trip for car commuting trips. At the time, the incentive program was innovative in several ways. First, the multi-level collaborating road authorities decided to encourage people to actively start e-cycling for daily commuting instead of only favoring the purchase of e-bikes and e-bike ownership. Second, the technique of GPS-tracking by mobile phone was introduced to monitor participants' behavior during the program. At that time, GPS-tracking for academic research had mostly been done by dedicated GPS-tracking devices. For the B-riders program, dedicated Android and iPhone applications for mobile phones were developed to track participants' behavior to allow for the provision of monetary in addition to social feedback based on individual e-cycling performance. With the aim to relieve participants and maximize trip registration for this study automated movement detection was integrated into the applications, where a dedicated start/stop button was initially preferred by the program management. Third, during the program, participants were obligated to complete three online surveys concerning their commuting habits, behavioral intentions, satisfaction with travel, and spatial context. These three surveys were specifically developed for the analyses reported in this thesis to measure longitudinal changes. At the start of the program, participants were questioned on their habitual commuting behaviors and their intentions to start using their e-bike for commuting purposes; after one month and six months, the same participants were questioned on their actual e-bike use while commuting. This process resulted in a three-wave longitudinal dataset with detailed indicators for sociodemographic data, multimodal travel behaviors, and (e-)cycling experiences. Figure 1.3 shows the longitudinal research approach.

In the early phase of the program, some doubts arose about the potential success of the program in terms of number of car commuters willing to actively change their car commuting behaviors. Recruitment conditions were set for which commuters had to travel to work by car on a minimum of 50% of their working days per week. The participants had to meet four other recruitment conditions: (1) having a minimum commute distance of at least 3 kilometers, (2) age 18 to 65 years old, and (3) working in the province of North-Brabant and (4) having purchased an e-bike at the start of the program. In the program initially developed to reduce regional peak-hour car congestion, a differentiation between peak and off-peak e-cycling compensation was introduced amounting to €0.15 per kilometer and €0.08 per kilometer, respectively. Participants were invited to participate for 12 months and could receive a maximum total of €1,000 (one thousand euro) in financial incentives per person. All potential participants were recruited using newspapers and online social media.

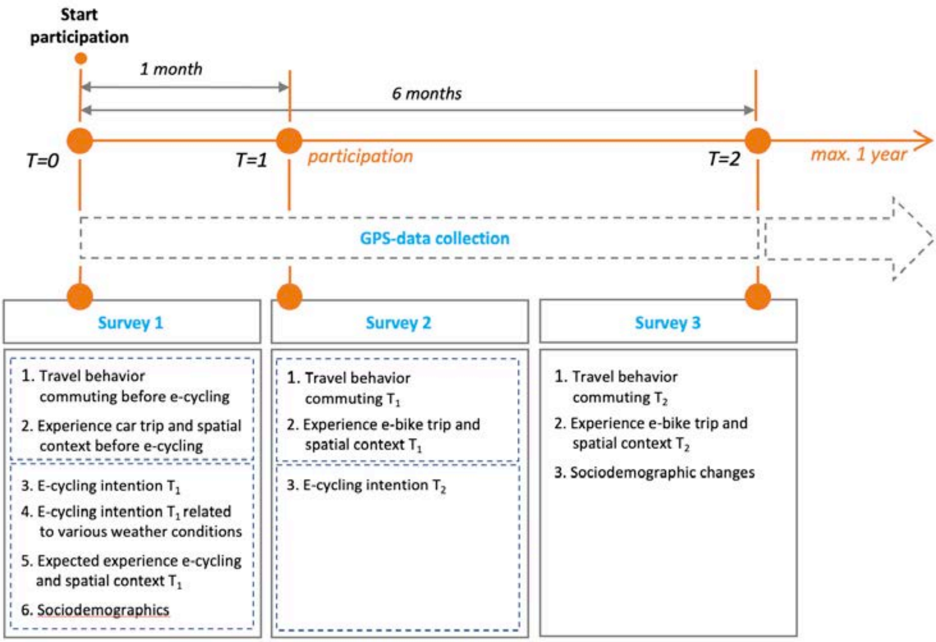


Figure 1.3. Overview of longitudinal research approach

The spatial data of the built environment used for the commuting characteristics were derived from a digital road network from the OpenStreetMap (OSM) that had been updated at the end of 2013 and corresponded to the timing of the B-Riders program combined with the postal codes (6sixdigits) of the home and main work locations. Also, the urbanization level of the home location was also derived from the postal code. Notably, none of the home locations was situated in the highest urbanization level (address density of 2,500 or more inhabitants).

By using an integrated data imputation tool, Trace Annotator (Feng and Timmermans, 2014; Feng and Timmermans, 2019), all collected GPS data were divided into journeys and stages (segments). The tool imputes the specific travel purpose, such as work, shopping, and social and recreational activities for each journey based on location of facilities and information from self-reported data about facility locations. Next, the number of different modes of transportation (stages) that were used during one relocation in addition to the specific mode of transportation per stage were determined. A total of 242,179 journeys and 355,996 stages were recorded.

To relate the day-to-day e-cycling performance of all participants as recorded with GPS data under different weather conditions, hourly meteorological data (air temperatures, wind speeds, and total precipitation), which was directly related to the available GPS data, for the province of Noord-Brabant were obtained from the Dutch Meteorological Institute (KMNI, 2014) from January 2014 to mid-September 2014. The province of Noord-Brabant is situated in the Southern

Netherlands, has 5,081 km2 in land surface, and is covered by the following three meteorological stations: (1) Gilze-Rijen (51° 34’N, 04° 56’E), (2) Eindhoven (51° 27’N, 05° 23’E), and (3) Volkel (51° 39’N, 05° 42’E). The region can be characterized by a warm to temperate (maritime) climate (Geiger and Pohl, 1954) with mild winters (average minimum air temperature, 7.1 °C), warm summers (average maximum air temperature, 16.3 °C), and relatively stable year-round total precipitation patterns (KNMI, 2014). To link travel behavior to meteorological data, participants’ home postal codes were assigned to one of the three weather stations.

Table 1.1 summarizes the general characteristics of the 635 participants who participated for at least a month in the B-Riders program. Next to the total number of commuters, the table shows a distinction between car commuters and multimodal commuters. The difference between both groups is the habitual conventional cycling before the start of participating in the program. Multimodal commuters already used the conventional bicycle on some days to cycle to work. Half of the participants were aged 50 or over. The gender distribution percentage of the participants in addition to car ownership was relatively balanced, and the sample was skewed to a higher educated population. In cases in which participants had to report on subjective health status, two-thirds indicated that their physical health status was good or excellent. The household composition was skewed to couples with children at home for which over 55% of the population worked five days a week or more. As the e-bike is regarded as a sustainable alternative mode of transport for the mid-range distances, the home to work cycling distance was well distributed in percentage terms. Urbanization levels of the home location mostly ranged from moderate to non-urbanized.

Table 1.1. Description of 635 participants participating in the B-riders program for at least one month.

Variable	Category	number	all commuters	car commuter	multi-mode commuters
Age	25-39 years old	84	13%	16%	12%
	40-49 years old	231	36%	35%	37%
	50-64 years old	320	50%	49%	51%
Gender	Male	308	49%	44%	50%
	Female	327	51%	56%	50%
Education level	Lower education | primary & secundary	113	18%	17%	18%
	Vocational education	178	28%	27%	29%
	Higher education | (applied) scientific	344	54%	56%	53%
Subjective health status	Bad	84	13%	17%	12%
	Neutral	125	20%	19%	20%
	Good	208	33%	33%	33%
	Excellent	218	34%	31%	36%
Car ownership	1 car	316	50%	45%	52%
	2+ cars	319	50%	55%	48%
Net household income (in € per month)	< 3,000	225	44%	36%	47%
	3,000 - < 4,000	187	36%	40%	35%
	> 4,000	102	20%	24%	18%
Household composition	Single	47	7%	8%	7%
	Single parent	17	3%	3%	3%
	Couples without children at home	214	34%	37%	32%
	Couples with children at home	357	56%	52%	58%
Urbanization level at home postal code	Highly urbanized	100	16%	11%	18%
	Moderate urbanized	151	24%	27%	22%
	Less urbanized	195	31%	31%	31%
	Not urbanized	189	30%	31%	29%
Cycle distance home - work	0-5 km	33	5%	2%	7%
	5<10 km	164	26%	18%	29%
	10<15 km	198	31%	33%	30%
	15<20 km	155	24%	28%	23%
	20+ km	85	13%	18%	11%
Commuting days a week	1-3 days	87	14%	24%	9%
	4 days	198	31%	31%	31%
	5+ days	350	55%	45%	60%
Flexibility working hours	Yes	377	59%	62%	58%
	No	258	41%	38%	42%

1.5 Thesis lay-out

This thesis consists of four empirical articles that reflect the sub-questions described above. All papers have been published or submitted to a peer-reviewed journal. The organization of the thesis follows the order of the research questions described in section 1.2. Chapter 2 presents the results of the evaluation of the modal shift from use of a car to e-cycling for daily commuting. This article was published in the Transport and Health in 2018. Chapter 3 presents the empirical article where the changes in persons' intention, behavioral change and intention-behavior consistency are explored during participation in the incentive program. This article was submitted to Cycling and Micromobility Research in 2023. Chapter 4 includes GPS data in addition to weather station data to describe the evaluation of weather effects on the e-bike use in daily commuting. This article was published in Transportation Research Part A in 2021. Chapter 5 describes the relation between travel behavior and well-being, where satisfaction with travel was introduced to measure e-cycling experience trips, routes, and spatial context. This article was published in Travel Behaviour and Society in 2019. Finally, Chapter 6 discusses the answers to the research questions and provides recommendations for further research and policy practice. An overview of the thesis structure, including the research design and studies in the chapters, is shown in Figure 1.4 below.

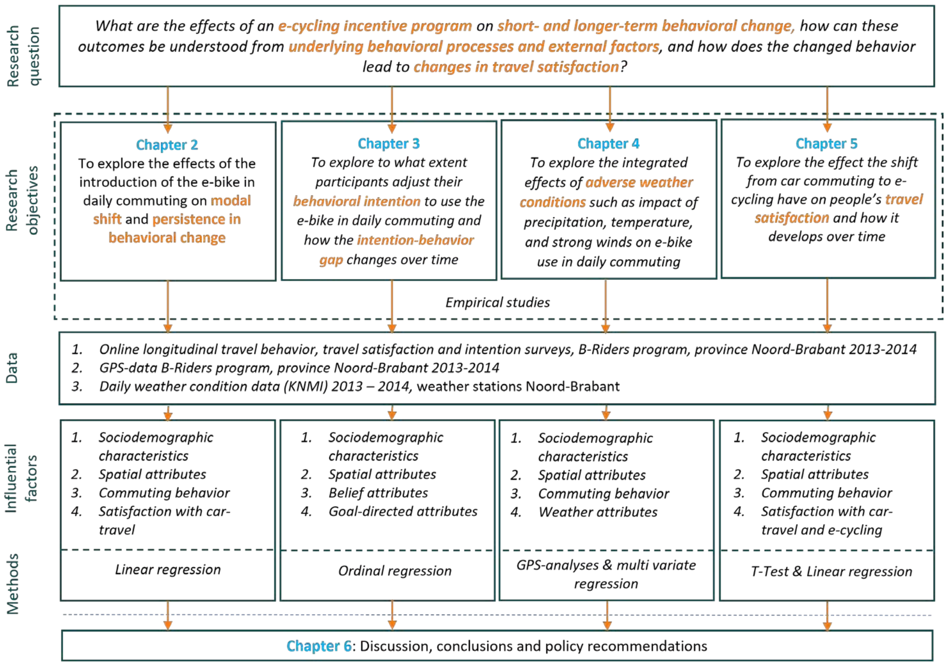


Figure 1.4. Thesis research design

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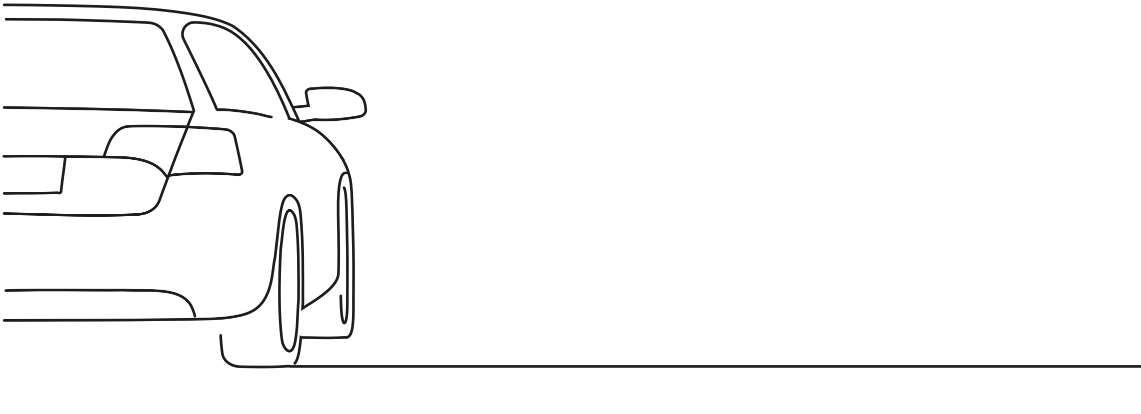
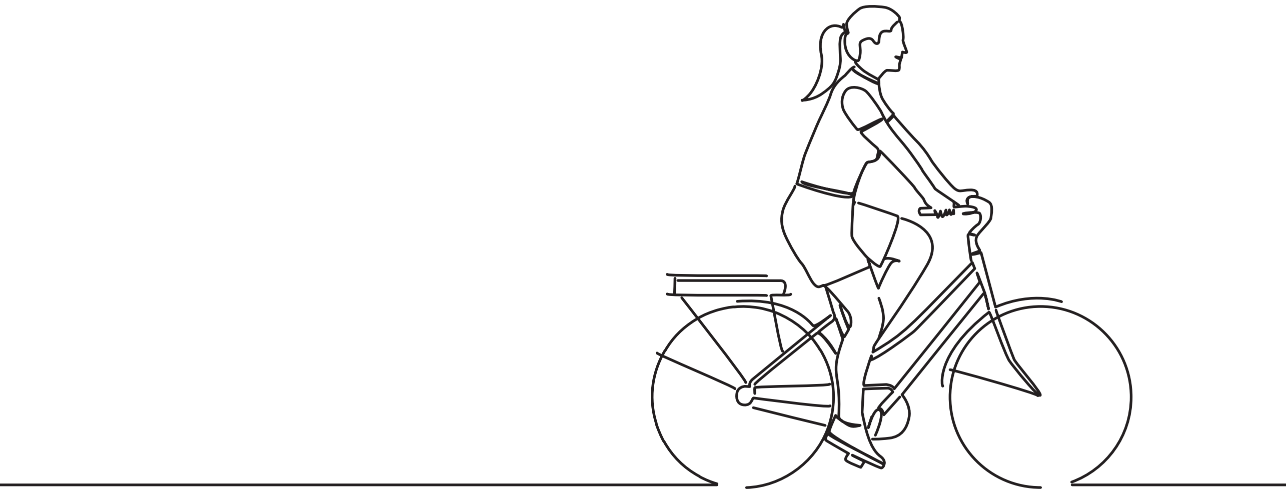


CHAPTER 2

Transition to E-Cycling in daily commuting: evaluation of an incentive program to stimulate the shift from car commuting to e-cycling in the Netherlands



Abstract

This paper reports on the effects of an e-cycling incentive program in the province of Noord-Brabant, The Netherlands, in which commuters could earn monetary incentives when using their e-bike. The study used a longitudinal design allowing to observe behavior change and mode shifts. The program appeared to be highly effective in stimulating e-bike use, as one month after the start of the program, the share of commute trips made by e-bike increased from 0% to 68%, with an increase up to 73% after half a year of participating. The environmental, congestion and health benefits of this shift are however mixed. Half of the e-bike trips substitute car trips, with positive effects on environment, congestion and health. The other half substitutes conventional cycling trips, implying fewer health benefits. Our analyses further suggest that distance is an important factor for adopting e-cycling, where e-bike has a larger acceptable distance than a conventional bike. Nevertheless, we observed that the likelihood to use the e-bike decreased as commuting distance increased. Multivariate analyses suggest that a shift to e-cycling is affected by age, gender, physical condition, car ownership and household composition. Our study did find support for the hypothesis that having a strong car-commuting habit decreases the probability of mode shift to a new mode alternative. In contrast, multimodality may increase the likelihood of e-bike use as a result of openness to other travel options and a more deliberate mode choice. Lastly, dissatisfaction with the current travel mode positively influences mode shift towards the e-bike. Our results imply that stimulating e-cycling may be a promising way of stimulating physical activity, but that it will be most effective if targeted at specific groups who are not currently engaging in active travel.

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2.1 Introduction

In recent years, there has been growing interest in the role of the bicycle in Western urban transport systems as an alternative to cars (Fishman and Cherry, 2015; Pucher and Buehler, 2012). Cycling has positive impacts on not only the environment, but also health through increased physical activity (Akar and Clifton, 2009; Badland and Schofield, 2008; Sugiyama et al., 2008). In areas with a high dependence on cars (e.g., the US), utilitarian cycling is often considered a fringe activity (Pucher et al., 1999; Moudon et al., 2005). Across European cities, however, non-motorized trips account for 10 to 48% of the total number of trips travelled (Rietveld and Daniel, 2004). In the Netherlands, cycling is a very popular mode of travel, accounting for 26% of all national trips (KiM, 2015). Of all trips shorter that 7.5km, which is 70% of all trips, 35% are made by bicycle. Despite this high share of cycling trips, there is still considerable potential for an increase in cycling.

Extensive research has identified determinants of cycling to work (e.g., Heinen et al., 2010, 2012; Vandenbulcke, 2011; Gatersleben and Appleton, 2007). These studies indicate that apart from cultural and societal factors, important factors that influence cycling behavior include personal and household characteristics, topography, distance, and time limitations. Various studies have shown that people who live close to their workplaces (< 5 km) are significantly more likely to use bicycles to commute than those with longer commutes (Kingham et al., 2001; Dickinson et al., 2003; Krizek 2010). The unattractiveness of utilitarian cycling for longer distances is related to physical effort (sweating) and the limited speed and range.

Bicycle-style e-bikes (i.e., bicycles assisted by electric motors) could potentially mitigate these factors given the lower physical effort required, higher speed, and greater range compared to regular bicycles (MacArthur, 2014, Dill and Rose 2014). Thus, e-bikes offer new modal shift opportunities in daily commuting. A shift from car commuting to using e-bikes has positive effects in terms of both sustainability and health. E-bikes are 18 times more energy efficient than car travel (Shreya, 2010). Physical activity levels during e-bike use are lower than in conventional cycling but markedly higher than in car use (Sundfør, 2017; Simons et al., 2009).

E-bikes have attracted a considerable amount of research attention (Fishman and Cherry, 2015; Rose, 2012; Dill and Rose 2014; MacArthur et al., 2014; Popovich et al., 2014; Jones et al., 2016). To date, only a few studies have investigated the factors influencing e-bike use. Various studies show that demographic characteristics like age, education, and income influence e-bike use (Popovich et al., 2014; MacArthur et al., 2014). Compared to traditional bike users, e-bike users are older, have a higher income, and have a higher educational level. Given the higher speed and lower effort associated with e-bike use compared to conventional cycling, e-bike trips are longer and tend to be made for a greater variety of purposes (Langford et al., 2013).

Replacing car travel with e-bike use is a key motivation for e-bike purchase in North America and Australia (Johnson and Rose, 2013; MacArthur et al., 2014; Popovich et al., 2014). The studies suggest that e-bike ownership indeed reduces the number of car trips. In the context of the first e-bike sharing program in North America, Langford et al. (2013) found that 11% of all e-bike trips would have previously been made using cars. A survey conducted among Northern-American e-bike users shows an increase of cycling at least once per week from 55% among those owning a conventional bike to 93% among those owning an e-bike (MacArthur et al., 2014). In addition, 45% use the e-bike for commuting as the primary reason. Reported reasons for e-cycling include greater range, easier acceleration, higher speed, and easier ascent of hills. Norwegian research shows that the percentage of cycling trips increased from 28% to 48% when people were provided with an e-bike (Fyhri and Fearnley, 2015).

Although the studies provide insights into the adoption rate of e-cycling and its impact on the reduction in trips by other travel modes, there is limited information on the factors that influence the use of e-bikes and their substitution for other travel modes. Only recently, a rather methodological study has been done on the substitution of travel modes related to e-bike ownership using data from a general mobility study (Kroesen, 2017). This is partly due to the fact that interventions in which travelers were encouraged to switch to or use e-bikes typically result in small samples or limited periods of time (Plazier et al., 2017) that do not allow extensive testing of influential variables using multivariate techniques. One recent study used qualitative methods that do allow the disentanglement of the effects of influential factors on e-bike use, but they do not allow for generalization of the results (Jones et al., 2016).

This study contributes insights into the actual behavioral responses to introducing e-bikes based on a unique large-scale (n = 547) and longitudinal dataset. The adoption of e-cycling in daily commuting was recorded in a reward-based e-cycling incentive program involving car commuters in the Netherlands. The data allow for exploring the actual effects of a wide array of factors that influence the extent of modal shift toward e-bikes. According to the literature on cycling and e-bike use, these variables include personal and household characteristics, work-related circumstances, and spatial characteristics (Fishman and Cherry, 2015, Heinen et al., 2010, 2012, Plazier et al. 2017).

However, given the longitudinal nature of our data, we add two factors that represent path dependency to our analysis. First, we assume that one's travel behavior prior to the incentive program influences the extent of using e-bikes in the program. Past behavior or habits have frequently been demonstrated to predict future behavior better than measures of intention and attitude (e.g., Bentler and Speckart, 1979; Ouellette and Wood, 1996). Verplanken et al., (1997, 1998) found that participants with a strong habit towards a particular travel mode acquire less information and use less elaborate choice strategies compared to participants with a weak habit. Likewise, it can be expected that those with a weaker habit who already combined commuting by car occasionally with other modes would be more open to using alternative travel modes and willing to try new travel options.

A study on mobility behavior among free-floating car-sharers compared to non-car sharers confirms this (Kopp et al., 2015). People with multimodal travel behavior (i.e., not always choosing the same mode for each trips) in the baseline situation were more willing to consider and use new transport options such as car sharing. Likewise, we expect that participants with multimodal commuting behavior prior to the program world be more willing to adopt e-cycling and use it more frequently. A related consideration is that e-cycling bears resemblance to conventional cycling in terms of propelling and maneuvering the vehicle as well as exposure to and experiencing the weather, landscape, and traffic conditions. Thus, those who occasionally cycle to work prior to the program may be expected to use e-bikes more frequently in the program.

Second, we predicted that participants' evaluations of their commute prior to the program would impact the extent of shifting toward e-bike use. In particular, if the car commute is experienced as less pleasant, it is predicted to lead to a higher frequency of using a new alternative mode. Various scholars outside the transportation area suggest that affect may drive behavioral change. Russell (2003) describes how individuals' affective states and a core driver of action in the sense that they seek to move away from negative affective states (avoidance) and seek positive affective states (approach). In a similar way, negative affective states associated with a certain current travel mode may trigger individuals to explore and use alternative methods of travel, leading to better affective outcomes. Another indication of the relevance of affect related to current behavior is obtained from the Extended Model of Goal-directed Behavior (EMGB) (Perugini and Conner 2000). EMGB extends existing attitudinal behavioral models by adding the element of volition originating from individuals' specific goals.

Along with cognitive factors such as attitude and perceived norms, EMGB poses that anticipated emotion is a driver of decisions, such as those related to environmental behavior. This mechanism also suggests that negative affect associated with one choice outcome based on previous experiences may lead to an increased likelihood of changing one's behavior. Based on these notions, this study tests the extent to which satisfaction with the current car commute impacts frequency of e-bike use as an alternative mode.

The contribution of this study is that it provides insight into the factors that determine the frequency of e-bike use based on a large longitudinal dataset. It tests typical factors related to socio-demographic characteristics, spatial setting, and work organization, as well as the extent that travel behavior and travel satisfaction prior to the behavior change influence the frequency of e-bike use. Finally, the study investigates e-bike use and its determinants within one month and six months after the intervention to test whether e-bike use and its determinants change over time.

2.2 Materials and methods

2.2.1 Data collection

To stimulate switching from cars to e-bikes, the province of Noord-Brabant in the Netherlands implemented an e-cycling incentive program ("B-Riders") aimed at car commuters in 2013. Participants were recruited individually to take part in the program in an open call by several media channels (newspapers, social media, newsletters of companies). To stimulate the use of e-bikes instead of cars, participants receive monetary compensation depending on their e-bike use while commuting. To reduce car congestion, the monetary incentive was set at €0.15 per kilometer during the peak hours and €0.08 per kilometer in the off-peak hours. Participants could earn a maximum of €1.000 (one thousand euros) per person overall based on the amount of kilometers cycled multiplied by the incentive.

E-bike use was monitored through a smartphone app that tracks e-cycling behavior. Given the average e-cycling commute distance, it would take up to a year to reach the maximum reward, implying that the incentive is effective for a long period. Participants in the program had to meet three conditions: (i) conducting at least 50% of their total weekly work trips by car before entering the program, (ii) having a commute distance of at least 3km, and (iii) being between 18 and 65 years old and working in the province of Noord-Brabant.

Three questionnaires were used to measure behavioral change, which all participants were obliged to complete. The baseline questionnaire (T0) recorded the travel modes used for commuting during one week before entering the program. Participants reported the frequency of days of choosing a specific main mode of transport for commuting on an average week before purchasing their e-bike. The options for the main mode of transport were car, carpool, motor, bus, tram, metro, moped/scooter, bike, and walking. In addition, respondents reported their satisfaction with current car travel to work and a set of personal and household characteristics.

Satisfaction with the car commute trip was measured using the Satisfaction with Travel Scale (STS) (Ettema et al., 2011). Consistent with theories on subjective well-being, this scale uses both cognitive and affective items. To measure affective well-being, the endpoints of each scale are defined as combinations of the valence/activation dimensions of the affect circumplex (Västfjäll and Gärling, 2007). Six scales were designed, of which three distinguish between positive deactivation (-3) (e.g., relaxed) and negative activation (3) (e.g., time pressed), and three which distinguish between positive activation (3) (e.g., alert) and negative deactivation (-3) (e.g., tired). Another three items measure the quality of travel and tap cognitive appraisal of the commute trip. The order between the ratings scales was counterbalanced. The items included in the STS are summarized in Table 1. Scores for satisfaction with travel were constructed for each respondent by averaging the ratings for each of three subscales.

Finally, in addition to personal and household characteristics like age, gender, education, income, and composition, participants reported their physical condition on a range of "very bad" to "very good" on a seven-point Likert scale. Based on the zip code of the home location, the degree of urbanization and the actual cycle distance using the available cycle network were derived. A follow-up questionnaire was administered one month after the start of participation in the program (T1). It included the same questions about frequency of travel modes used for commuting (including the e-bike) and satisfaction with the e-bike commute. The third and final questionnaire was held six months after the start of participation in the program (T2). It was similar to the questionnaire at T1 and included questions about the frequency of travel modes used for commuting (including the e-bike) and satisfaction with the e-bike commute. The study is based on responses from 547 participants, who fully completed all three questionnaires. The participants were split into two groups of varying commute behavior prior to the program: those who only commuted by car during the baseline measurement (n = 172) and those who used multiple modes for commuting (n = 375).

Table 1. End points of the Satisfaction with Travel scale.

Positive deactivation-negative activation (items 1-3)	
… I feel stressed	… I feel calm
… I feel hurried	… I feel relaxed
… I feel worried arriving too late	… I feel confident arriving on time
Positive activation-negative deactivation (items 4-6)	
… I'm bored	… I'm enthusiastic
… I'm tired	… I'm alert
… I'm fed up	… I'm engaged
Cognitive evaluation (items 7-9)	
… Travel was laborious	… Travel was prosperous
… Travel was uncomfortable	… Travel was comfortable
… I experience my trip as bad	… I experience my trip as optimal

2.2.2 Sample descriptives

The baseline survey included questions about personal and household characteristics like gender, age, educational level, income, car ownership, household composition, and subjective physical condition. Based on reported home and work locations, the levels of urbanization of both the work and home locations and cycling distance were derived from land use statistics and Open Street Map. Table 2 shows the sample characteristics of all participants (both unimodal car commuters and multimodal car commuters).

Table 2 shows that more than half of the sample is between 50-64 years old and highly educated. The age is in line with literature reporting that e-bikes are especially popular among older age cohorts. Almost 70% of the sample reported good or excellent physical condition. More than 50% of the sample belongs to the category of "couples with children." Half of the sample owns two or more cars, and the majority (57%) falls in the higher income categories (> 3000 EURO/month). 78% of them had commutes longer than 10km, suggesting that e-bikes may be an important alternative travel mode that offers acceptable travel times and is useful for longer distances. About 60% had flexible working hours.

Table 2. sample composition.

Variable	Category	All participants	Unimodal car commuters	Multimodal car commuters
Age	25 - 39 years	12%	15%	11%
	40 - 49 years	37%	34%	38%
	50 - 64 years	51%	51%	51%
Gender	Male	48%	45%	50%
	Female	52%	55%	50%
Education	Low	13%	17%	17%
	Medium	28%	26%	28%
	High	58%	58%	55%
Physical condition	Physical condition bad	14%	17%	12%
	Physical condition neutral	18%	17%	19%
	Physical condition good	33%	33%	33%
	Physical condition excellent	35%	33%	36%
Car ownership	1 car	50%	45%	52%
	2+ cars	50%	55%	48%
Household income (in € per month)	< 3.000	43%	35%	46%
	3.000 - < 4.000	37%	42%	35%
	> 4.000	20%	23%	18%
Household composition	Single	7%	6%	7%
	Single parent	2%	2%	2%
	Couple without children	35%	40%	33%
	Couple with children	56%	52%	58%
Residence urbanization	(very) strong Urbanized	15%	11%	17%
	moderate urbanized	23%	26%	21%
	Less urbanized	32%	33%	31%
	Not urbanized	30%	30%	30%
Cycle Distance (per commute trip)_	0 - 5 km	4%	1%	5%
	5<10 km	19%	13%	22%
	10<15 km	31%	30%	31%
	15<20 km	29%	30%	28%
	20+ km	18%	26%	14%
Commuting days a week	1 - 3 days	14%	26%	9%
	4 days	33%	31%	33%
	5+ days	53%	43%	58%
Flexibility working hours	Yes	60%	62%	59%
	No	40%	38%	41%

The unimodal car commuters and multimodal car commuters do not differ substantially in most characteristics. However, the car-only commuters have longer commutes and more often have two or more cars in the household. They also tend to have higher incomes. Finally, the number of travel days to work is less for car commuters compared to the other group, with 74% of car users travelling 4 days or more to work and 91% doing so among multimodal car commuters.

2.2.2.1 Satisfaction with car travel

Table 3 shows the distribution of satisfaction scores with car commuting. For each participant, the scores for all three subscales were calculated by averaging the scores (ranging from -3 to 3) on the three items related to each subscale.

Table 3. Satisfaction with car-commuting (T0).

Variable	Category	All participants	Unimodal car commuters	Multimodal car commuters
Positive deactivation - negative activation	x < - 1.0	8%	8%	9%
	-1.0<=<1.0	40%	35%	42%
	x>=1.0	52%	58%	49%
Positive activation - negative deactivation	x < - 1.0	10%	9%	11%
	-1.0<=<1.0	59%	59%	60%
	x>=1.0	30%	33%	29%
Cognitive evaluation	x < - 1.0	6%	6%	6%
	-1.0<=<1.0	56%	47%	60%
	x>=1.0	38%	47%	34%

As might be expected, car-only commuters are more positive about the affective evaluation of car travel than multimodal car commuters. This is shown by the higher percentages of scores above 1.0 on both the positive activation and positive deactivation sub-scales. Regarding cognitive evaluation of the car commute, more car-only commuters are positive (47%) compared to multimodal-commuters (34%) with a score above 1.0. Multimodal users might be less positive about their car commuting because of their experience with alternative modes like cycling, or they might have already partly switched to alternatives in an earlier stage because of a negative evaluation. Overall, however, multimodal car commuters appear to be mostly positive or neutral about their car commute, and only a small number have negative scores on the affective or cognitive scales. Notably, a small number of car commuters also have negative scores on the various dimensions of travel satisfaction, suggesting that introducing a new travel mode may help them to improve their travel satisfaction.

2.2.3 Analyses

To explore the responses to the e-bike incentive program and the factors influencing the responses, we carried out descriptive analyses of the modal split across all trips made over one week by participants before (T0) and one month after the start of the program (T1). To investigate the effect of commute distance and the difference between unimodal and multimodal car commuters, analyses were split between both dimensions. Next, we carried out multivariate regression analyses of e-bike usage frequency at T1 and T2 with personal characteristics, household characteristics, commute characteristics, and satisfaction with the car commute as explanatory variables. This allows us to draw conclusions about the factors that lead to a positive response to the e-bike incentive program.

2.3 Results

2.3.1 Descriptive analyses

Table 4 shows the modal split as percentages of weekly commuting trips per mode compared to the total number of weekly commuting trips for T0 and T1. Before the program (T0), 61% of all commuting trips were made by car, 33% were made by regular bicycle, and 6% were made by other modes. Thus, a reasonable percentage of participants had already experienced alternative travel modes. For all categories, as distance increases, the percentage of car use also increases from 51% (distance 5-10 km) to 71% (distance > 20km). Logically, the effect is also seen for the multimodal car commuters, where car use increases from 31% to 51% from the shortest to the longest distances.

Table 4. Modal split (commuting) per distance class at T0 and T1.

		T0				T1				T2			
All participants	n	car	bike	e-bike	other	car	bike	e-bike	other	car	bike	e-bike	other
0-5 km	20	42%	47%	0%	11%	18%	0%	80%	2%	12%	0%	87%	1%
5<10 km	105	55%	42%	0%	3%	24%	0%	74%	2%	18%	0%	80%	2%
10<15 km	167	61%	34%	0%	4%	27%	1%	70%	2%	23%	1%	74%	3%
15<20 km	156	63%	31%	0%	6%	32%	0%	65%	3%	26%	1%	71%	3%
20+ km	99	72%	21%	0%	7%	31%	1%	63%	5%	30%	1%	64%	5%
Total	547	62%	33%	0%	5%	28%	1%	68%	3%	24%	1%	73%	3%
Unimodal car commuters	n	car	bike	e-bike	other	car	bike	e-bike	other	car	bike	e-bike	other
0-5 km	2	100%	0%	0%	0%	30%	0%	70%	0%	10%	0%	90%	0%
5<10 km	22	100%	0%	0%	0%	31%	1%	65%	3%	22%	0%	78%	0%
10<15 km	52	100%	0%	0%	0%	27%	1%	70%	1%	23%	0%	73%	4%
15<20 km	51	100%	0%	0%	0%	38%	0%	61%	1%	36%	0%	62%	1%
20+ km	45	100%	0%	0%	0%	40%	0%	60%	0%	34%	1%	62%	3%
Total	172	100%	0%	0%	0%	34%	0%	64%	1%	29%	0%	68%	2%
Multimodal car commuters	n	car	bike	e-bike	other	car	bike	e-bike	other	car	bike	e-bike	other
0-5 km	18	35%	52%	0%	12%	16%	0%	81%	2%	13%	0%	86%	1%
5<10 km	83	43%	53%	0%	4%	22%	0%	76%	2%	17%	1%	80%	2%
10<15 km	115	45%	48%	0%	6%	27%	1%	69%	3%	24%	1%	74%	2%
15<20 km	105	47%	45%	0%	8%	29%	0%	67%	4%	21%	1%	75%	3%
20+ km	54	51%	38%	0%	12%	24%	1%	65%	9%	27%	2%	66%	6%
Total	375	46%	47%	0%	7%	25%	1%	70%	4%	21%	1%	75%	3%

Table 4 also shows that participation in the program leads to a strong modal shift. Overall, car use drops from 62% to 28%, conventional bicycle use drops from 33% to 1%, and e-bike accounts for 68% of all commute trips at T1. Hence, e-bikes substitute for cars and conventional cycling to about the same extent. E-bike use is highest for the shortest distances (0-5 km: 80%) and decreases with distance, but it still accounts for 63% of trips longer than 20 km. At T2, the use of e-bikes increased further, with car use dropping further to 24% and e-bikes accounting for 73% of all commute trips. The further increase in e-cycling is particularly shown in the distance range of 0-20km.

In the group of unimodal car commuters, the percentage of e-cycling at T1 is lower (64%) than in the other group (70%) but still very substantial. This difference remains at T2, where the shares of e-cycling have further increased to 68% and 75%, respectively. The reduction in car use is much higher for unimodal car commuters (-66%) than for multimodal car commuters (-21%) at T1 and T2 (-71% and -25%, respectively).

For both groups, there were significant decreases in car use and the adoption of e-cycling for all distance ranges, but the effect tends to diminish with distance, implying that e-bikes provide the best alternative to car travel for distances less than 15 km. For the car-only commuters, this implies a reduction in the substitution of car use with increasing distance. For the multimodal car commuters, the reduction of car use is more or less independent of distance because e-bikes also substitute for conventional bicycle use.

3.2 Regression models of e-bike frequency

To explore the effects of a wide array of factors on the transition to e-bikes, multivariate regression models were used with the number of e-bike commuting trips at T1 and T2 as dependent variables. Commute distance, satisfaction with car commuting before entering the program, and the percentage of conventional cycling at T0 were also investigated as independent variables in addition to personal and household characteristics (gender, age, physical condition, income, education, household composition, and car occupancy), as well as work-related circumstances (urbanization level, flexibility, and travel days to work). Furthermore, we included commute frequency in order to scale the e-bike frequency to the total number of commutes per week. Table 5 shows the estimation results of the regression analyses for the total group of participants, car-only commuters, and multimodal commuters.

All models are highly significant with acceptable goodness-of-fit measures. Overall, the factors that influence e-bike use at T1 and T2 are similar, although some subtle differences emerge. The estimations indicate that at T1 and T2, men use e-bikes more often than women. However, this effect is only observed for the multimodal commuters. A potential explanation is that women are more bound to their cars as they combine their commute trip with household-related stops such as dropping off or picking up children and grocery shopping.

Participants with bad physical condition e-cycle significantly less than all other participants, but there is no effect of having a neutral or good level of physical condition (relative to excellent condition). Apparently, physical condition is not an obstacle for riding an e-bike unless one's physical condition is very bad. Remarkably, this effect is weaker in effect size and significance at T2. This may be due to the fact that the health of participants improves as a result of the shift to e-cycling, as shown in an accompanying paper describing the project (De Kruijf et al., 2018).

As expected, having only one car in the household correlates with a higher frequency of e-cycling relative to those who have two or more. However, this effect is observed for only multimodal car commuters at T1 and T2. This makes sense as car-only commuters have access to a car every day by definition, and as a consequence, the number of cars in the household has no effect. For T2, we find an income effect for the car-only commuters. Lower-income participants have a higher e-cycling frequency. This may be explained by the higher value they place on the financial incentive, but it is not clear why this effect is not observed for multimodal commuters and at T1.

Single individuals e-cycle less compared to couples with children, while couples without children e-cycle more. According to other studies (Popovich et al., 2014; MacArthur et al., 2014), older couples without children at home are generally known as frequent e-cyclists. In addition, having to take care of children may involve more complex trip patterns, which are more easily made by car and less easy to do by e-bike. However, these effects disappear at T2. It is possible that during several months of participation, participants find ways to organize their household obligations and activities such that the e-bike commute is no longer hampered.

Although descriptive statistics showed a decreasing trend of e-cycling with distance, only the shorter distances (0-10km) show a significant impact on e-cycling frequency in the estimation results of T1 and T2. Logically, e-cycling frequency is higher when there are shorter distances. However, this effect is not significant for the car-only commuters. This outcome reflects the descriptive results in Table 4, which show lower variation of the modal share of e-bikes between different distances. For multimodal car commuters, the pattern of e-bike use could possibly follow their conventional cycling behavior (through substitution), which is highly dependent on distance. As expected, the number of commute days to work positively influences e-cycling, basically indicating that the number of e- bike trips increases with the number of trips in general. This variable serves as a control variable in order to obtain unbiased effects of the other variables.

The frequency of conventional cycling at T0 has a positive effect on the number of e-bike trips in both the total model and in the model of multimodal car commuters and at T1 and T2. There are multiple possible explanations for this effect. First, since e-cycling is similar to conventional cycling in terms of the type of activity (although less intensive), exposure to the environment and weather, and parking, it is likely that those with a preference for cycling who cycle more at T0 will also be more likely to use e-bikes at T1.

Second, using multiple modes at T0 (including cycling and cars) may be an indicator of openness to alternative travel options and a more deliberate mode choice process from day to day. Such an attitude may also lead to a more frequent choice of the e-bike if this is an attractive option. Third, having no organizational constraints for cycling to work, such as having to drop off family members, carrying equipment, or wearing cycling-unfriendly clothes, implies that e-cycling to work will also be easier to do. These factors also persist after six months.

Finally, satisfaction with the commute at T0 has a close to significant impact on using the e-bike at T1. No significant effects of the affective dimensions were found (positive activation and positive de-activation), suggesting that positive or negative emotions do not translate into a greater willingness to shift modes in this case. However, those with a more positive cognitive assessment of the car commute are marginally less likely to use the e-bike in the total model and the model of multimodal car commuters. Nevertheless, the effect is weak and is not found for car-only commuters and multimodal commuters separately or at T2.

Table 5. Regression analysis of e-cycling for total sample, car-only commuters, and multimodal car-commuters.

		T1						T2					
		Total		100%		Multimodal		Total		100%		Multimodal	
		B	Sig.	B	Sig.	B	Sig.	B	Sig.	B	Sig.	B	Sig.
	Constant	2.969	0.000	2.728	0.000	2.980	0.000	3.112	0.000	3.542	0.000	2.807	0.000
Age	25-39 years old	-0.265	0.084	-0.295	0.303	-0.274	0.145	-0.169	0.296	-0.475	0.112	0.000	0.998
	40-49 years old	-0.120	0.284	0.005	0.984	-0.133	0.292	-0.039	0.740	-0.105	0.685	0.048	0.716
Gender	Male	0.348	0.001	0.387	0.091	0.279	0.025	0.279	0.015	0.217	0.362	0.271	0.038
Fitness	fitness bad	-0.463	0.002	-0.689	0.025	-0.438	0.018	-0.366	0.023	-0.427	0.181	-0.377	0.051
	fitness neutral	-0.044	0.744	0.087	0.763	-0.114	0.459	-0.201	0.157	-0.425	0.160	-0.124	0.441
	fitness good	-0.015	0.894	-0.273	0.274	0.056	0.666	-0.097	0.412	-0.576	0.028	0.023	0.868
Car occu-pation	1 car per household	0.262	0.008	0.104	0.611	0.319	0.005	0.153	0.140	-0.235	0.271	0.282	0.018
Income	< 3.000	-0.060	0.607	0.327	0.207	-0.161	0.233	0.034	0.782	0.580	0.032	-0.122	0.388
	3.000 - < 4.000	0.021	0.858	0.072	0.753	-0.018	0.895	-0.097	0.430	-0.089	0.711	-0.142	0.324
Household composi-tion	Single	-0.698	0.002	-0.636	0.181	-0.830	0.002	-0.368	0.124	-0.418	0.399	-0.460	0.095
	Single parents	-0.679	0.040	-0.033	0.980	-0.807	0.027	-0.093	0.789	-0.634	0.639	-0.111	0.770
	Married	0.615	0.007	0.507	0.272	0.725	0.007	0.214	0.374	0.080	0.868	0.306	0.274
Urbaniza-tion	(very) strong urban	-0.033	0.821	0.298	0.391	-0.107	0.518	-0.142	0.362	0.079	0.828	-0.164	0.343
	moderate urban	-0.048	0.715	0.153	0.555	-0.120	0.442	-0.211	0.126	-0.313	0.247	-0.134	0.412
	little urban	-0.107	0.363	0.266	0.280	-0.216	0.113	-0.096	0.437	-0.088	0.732	-0.055	0.701
Cycle distance	0-5 km	0.732	0.008	0.530	0.728	0.646	0.027	0.899	0.002	1.482	0.351	0.853	0.005
	5<10 km	0.431	0.007	0.234	0.489	0.477	0.013	0.644	0.000	0.732	0.039	0.653	0.001
	10<15 km	0.162	0.251	0.458	0.085	0.056	0.752	0.324	0.029	0.536	0.054	0.273	0.138
	15<20 km	0.049	0.728	0.146	0.568	-0.014	0.935	0.213	0.151	0.024	0.927	0.346	0.061
Commuting days	1-3 days a week	-0.785	0.000	-0.575	0.038	-1.076	0.000	-0.837	0.000	-0.680	0.019	-1.079	0.000
	4 days a week	-0.421	0.000	-0.417	0.085	-0.405	0.001	-0.382	0.001	-0.420	0.095	-0.346	0.009
Habitual cycling	Cycle share	0.565	0.000			0.847	0.000	0.534	0.001			0.833	0.000
Satisfaction with (car) travel	Positive deactivation - negative activation	-0.005	0.922	-0.009	0.943	-0.006	0.919	0.021	0.708	0.082	0.521	0.005	0.938
	Positive activation - negative deactivation	-0.038	0.523	-0.053	0.673	-0.048	0.497	-0.066	0.301	-0.144	0.272	-0.055	0.461
	Cognitive evaluation	-0.106	0.068	-0.130	0.305	-0.088	0.191	-0.096	0.116	-0.136	0.304	-0.078	0.269
Goodness-of-fit (R2)		0.265		0.227		0.305		0.217		0.247		0.238	

2.4 Discussion

This paper reports on the effects of an e-cycling incentive program in the province of Noord-Brabant, the Netherlands, in which commuters could earn monetary incentives when using their e-bikes. The study uses a longitudinal design that can be used to observe behavior changes and mode shifts. The e-bike incentive program from which data was taken in this study provides a unique dataset that covers the recording of behavior over a year-long period. This allows us to test behavioral changes for not only the one-month period reported in this paper but also longer periods. Future research is planned to investigate longer-term behavioral processes, which will provide much needed insight into adherence to the mode shift and the extent to which personal and commute characteristics influence adherence.

The program was found to be highly effective in stimulating e-bike use, as 66% of the commute trips were made by e-bike at one month after the start of the program. However, the environmental, congestion, and health benefits of this shift are mixed. Half of the e-bike trips substitute for car trips and thus have positive effects on the environment, congestion, and health. The rest of the trips substitute for conventional cycling trips, implying less health benefits because e-cycling is less strenuous than regular cycling. However, Simons et al., (2009) showed that all three power settings on an e-bike provided a useful contribution in meeting minimum physical activity requirements. E-cyclists achieve the necessary physical activity to enhance health and reduce the chance of sedentary lifestyle diseases, despite the electrical assistance (De Geus et al., 2013). However, given the higher speed, e-cycling reduces the duration of physical activity in daily commuting. Nevertheless, it should be noted that this difference is context specific, and there may be less difference in speed between conventional cycling and e-bikes in more congested urban environments and without dedicated cycling lanes.

Some research suggests that cyclists spend more time on their e-bikes than if the e-bike was unavailable (MacArthur et al., 2014). This holds in particular for those using only cars for commuting before the incentive program. The substitution of conventional cycling with e-bike use might suggest that e-cycling is more attractive than conventional cycling. Sperlich et al. (2012) established that sedentary women in a small-scale experiment found e-cycling more enjoyable than conventional cycling, which alluded to the less cardiorespiratory effort involved. On the other hand, Ekkekakis et al. (2008) state that physical activity can have a positive effect on enjoyment, suggesting that there is an optimal level of intensity of physical activity in terms of affect. However, this optimum may be different for car users than for regular cyclists, who are better trained and enjoy the exercise. In interpreting the findings, it should also be kept in mind that behavior was recorded when the financial incentive for each kilometer e-biked was still in place. It is possible that e-bike use will diminish after the incentive period, which may also imply that commuters partly return to conventional cycling.

Our analyses also suggest that distance is an important factor for adopting e-cycling. While e-bikes increase the range of acceptable distance, we still see a decreasing effect of e-bike use according to distance as cars are still significantly faster and lead to savings in travel time with longer distances. We also found that the effect of distance differs between multimodal car commuters and those solely relying on cars to commute. The latter group appears to be less sensitive to distance in our study. The reduction of car use for the multimodal car commuters is more or less independent of distance because e-bikes also substitute for conventional bicycle use.

Multivariate analyses suggest that a shift to e-cycling is affected by gender, physical condition, car ownership, and household composition. No effect was found for the degree of urbanization, which was somewhat unexpected, as e-bikes might be more competitive in urban settings between cities and suburbs. However, the degree of urbanization referred only to the residential location and did not take into account the location of the workplace and the route between home and work.

Our study found that commuting behavior prior to the intervention influenced e-cycling frequency in that a higher cycling frequency is associated with a higher e-cycling frequency. As mentioned, this may be due to similarities between cycling and e-cycling, so that those with a preference for cycling also have a greater preference for e-cycling, greater openness to other travel options, or a lack of constraints for both cycling and e-cycling. In the current setup, we could not disentangle these factors. However, future research should address the various ways in which such path dependencies in travel behavior occur.

We found no clear impact of the experience of the car commute on e-cycling frequency. The marginally significant effect at T1 is an indication that the mode change is affected by the evaluation of the current mode and that avoidance (Russell, 2003) takes place to some extent. However, more research is needed to identify whether more substantial effects are at play for specific segments or based on specific aspects of the travel experience.

Altogether, the study suggests that incentive programs for e-cycling can be effective tools to relieve congestion and stimulate physical activity, but that care should be taken in regard to which groups are targeted. The greatest potential gain is among car-only commuters, as every e-bike trip substitutes for a car trip and not a conventional cycling trip. However, excluding multimodal car commuters may be practically difficult and lead to problems of fairness and acceptance. In terms of distance, the reduction of the share of car commuters is less for longer distances, but the effect on congestion, environmental impact, and physical activity is still very worthwhile. Hence, e-bike incentive programs can be targeted at both shorter and longer distance commuters.

From a policy point of view, our results imply that promoting e-cycling may be an effective way of stimulating physical activity with associated health effects. However, as the effects on physical activity and health strongly depend on mode use before the intervention, incentive programs should target groups that are currently not engaged in active travel (or are engaged to a limited extent). Among those not engaging in active travel before the program, physical condition appeared to be the only relevant predictor of e-cycling adoption. While those with a bad condition were least likely to adopt e-cycling, they will likely have the largest health benefit of doing so. This suggests that interventions should specifically focus on groups with bad physical condition by providing tailored information and support programs. In line with our hypotheses, we found that distance has a negative effect on the adoption of e-cycling, but this effect is only slight, and the mode share of e-bikes is still very substantial (57%) for the longest distance category. As longer e-bike commute trips imply more physical activity, policy efforts should be directed at improving conditions for longer distance cycling - for instance, by creating dedicated infrastructure (such as cycling highways).

This study is a first step in investigating the potential of e-cycling in commute travel. More effort is needed to come to more general conclusions and further increase our knowledge about influential factors. First, the mode shift observed in this study was induced by an incentive as part of a program. It cannot be concluded that mode shifts in other contexts (e.g., without providing incentives or in different geographical contexts) will be comparable in size or be subject to the same influential factors. More longitudinal studies of e-bike adoption in a variety of contexts will be needed to answer these questions.

Second, the current study paid limited attention to route characteristics, which were only represented by distance. Obviously, aspects such as quality and safety of the cycling infrastructure, landscape, and aesthetics may be important factors in e-bike use, which can be targeted in policies. For instance, these characteristics may differ strongly between the Netherlands, which has an extensive cycling infrastructure, and North-American and the United Kingdom, where such infrastructure is often lacking. Route characteristics could be investigated based on GPS tracking of commute trips, which is available for our sample, and augmented with detailed information about land use, buildings, and vegetation.

Third, while our study provides valuable additional insights as compared to cross-sectional studies, it makes sense to study mode choice behavior over longer periods. Adherence to healthy behaviors (e-cycling in this case) is a crucial aspect for sustained positive health effects, and studies in other domains (Ettema et al., 2010) have shown that behaviors triggered by incentives are not necessarily sustained when the incentive ends. Finally, as noted, conventional cycling is also substituted by e-bike use. More research is needed to investigate what motivates cyclists to switch to e-bikes, how the experiences of cycling and e-cycling differ, and how these aspects differ between cyclists according to gender, age, fitness, and motivation.

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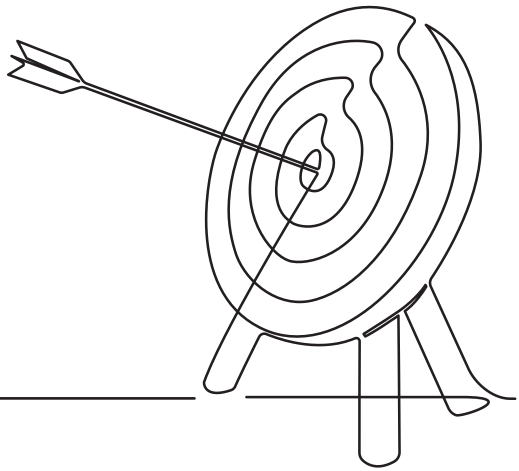
CHAPTER 3

E-cycling intention versus behavioral change: Investigating longitudinal changes in e-cycling intention and actual behavior change in daily commuting



Abstract

Modern cities and regions strive to maintain or improve economical accessibility, reduce the negative impact on the environment, and increase livability and safety for their citizens and visitors. Therefore, a behavioral change has to be brought about from car-dependent lifestyles to other forms of sustainable mobility. Based on previous research, the e-bike can be regarded as a sustainable alternative for mid-range (7.5 to 15 km) distances. Despite all advantages (e-)cycling brings to urban accessibility, the environment, personal health, and well-being, not all people regard the e-bike as a suitable alternative yet in their daily activity patterns. In addition to recent research on e-bike usage, satisfaction with travel, and the impact of weather circumstances, this study reports on changes in behavioral intention and actual e-cycling brought about by an e-cycling incentive program in the province of Noord-Brabant, the Netherlands. The impact of the program on the behavioral intention and the actual change to e-cycling was analyzed based on a longitudinal design of surveys on past, intended, and actual commuting behavior, home-work distances, and sociodemographic characteristics. Results show that a vast majority of people have a stable pattern of intention and intention-behavior relation within the period of participation in the program. Where a difference in intention and intention-behavior between commuters with and without regular cycling habits might be expected, results show similar trends. Regression analyses, adding beliefs (attitudes, perceived behavioral control, subjective norm), habits, and goal-related variables (goal perceived feasibility, goal desire, goal (positive and negative) anticipated emotions) do not show a pattern of significant relationship with changes in intention nor the intention-behavior gap. In general, the participants' behavior during the incentive program shows positive results in a behavioral change to e-cycling.

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Keywords: e-cycling, intention-behavior gap, e-bike, behavioral change, intention-behavior consistency

3.1 Introduction

In order to promote more sustainable forms of mobility, policymakers aim to stimulate a change in behavior from current car-dependent lifestyles towards the use of travel modes that produce less noise, pollution, and greenhouse gasses (Commission of the European Communities, 2007). To achieve the necessary behavioral change, cities invest in motorized alternatives such as public transport, and non-motorized modes of transport such as cycling and walking. Over the last decade, cycling has received a growing interest in Western urban transport systems as an alternative to car use (Fishman & Cherry, 2016; Buehler & Pucher, 2012). In the year 2021, policies to stimulate cycling got additional traction during the COVID-19 pandemic, as the strong reduction in car traffic and health risks associated with public transport increased people's willingness to cycle. Obviously, cycling has positive environmental impacts and positive health effects through increased physical activity (Akar & Clifton, 2009; Badland & Schofield, 2008; Sugiyama et al., 2008). Despite the positive arguments related to cycling as a sustainable option for commuters, many still choose to use other modes of transport.

With the introduction of the bicycle-style ((MacArthur et al., 2014; Dill & Rose, 2012) e-bikes (i.e., a bicycle with electric pedal assistance up to 25 km/h), factors like the required physical effort and greater range due to the higher speed compared to conventional bicycles offer new opportunities in the transition to sustainable mobility (Heinen et al., 2010; de Kruijf et al., 2018; Plazier et al., 2017). Compared to car travel, e-bikes are eighteen times more energy efficient (Shreya, 2010). Physical activity levels during e-bike use are lower than conventional cycling but markedly higher than during car use (Sundfør & Fyhri, 2017; Simons et al., 2009), implying that e-bike use also has positive health effects. Over the last couple of years, e-bikes have become more mainstream and popular, and extensive research has been conducted regarding various aspects of the use of the e-bike. Next to the effects of personal and technical factors such as gender, age, and perceived safety on e-bike use (Fishman & Cherry, 2016; Johnson & Rose, 2013; MacArthur et al., 2014; Popovich et al., 2014), the impact of e-bike promotion schemes on behavioral change has been investigated (de Kruijf et al., 2018; Kroesen, 2017; Plazier et al., 2017). Taken together, these studies suggest considerable potential for the e-bike to substitute for car use in commuting. Another relevant finding from previous research is that travel habits and previous experience play a significant role in e-bike use: those with a prior cycling habit are more likely to adopt and maintain e-bike commuting (de Kruijf et al., 2018).

A major challenge in bringing about a transition toward large-scale use of the e-bike in commuting remains to achieve actual behavioral change (and adherence to the changed behavior) of people to take up e-cycling. The challenge to achieve the behavioral change can be compared to other behavioral changes like increasing physical activity in general, changing to healthier eating patterns, and not smoking (Faries, 2016). The need to bring about behavioral change is especially apparent for programs to stimulate the use of conventional bicycles in daily commuting, such as bike-to-work days and public bicycle rental schemes (Buehler & Pucher, 2012; Pucher et al., 2010). Such programs typically recruit potential cyclists and stimulate them to cycle by providing information, support, and incentives, monitoring their behavior, and providing feedback.

While various studies have focused on the behavioral change brought about by e-cycling stimulation programs (Sun et al., 2020; Pucher et al., 2010), the underlying mechanism of behavioral change has received less attention. The widely known Theory of Planned Behavior (Ajzen, 1991) states that behavior is preceded by an intention toward this behavior, implying that behavior change is preceded by a change in intention. It is, however, also well documented that intention and behavior are often inconsistent because various factors prevent intention from being implemented (Sniehotta et al., 2005). In epidemiological studies, intention itself has already been proven to be a limited predictor of actual behavioral change (Faries, 2016; Norton et al., 2015; Grimmer & Woolley, 2014). Since policies to promote e-cycling affect e-cycling behavior via the intention to use the e-bike, insight into intention-behavior (in) consistency in this domain is important to design effective behavior change policies. Next, it can be argued that intentions, as well as the actual behavior, can change over time due to habituation, improvement of physical condition (De Kruijf et al., 2018), or other experiences during e-cycling. To better understand dynamics in e-cycling, insights into the intention-behavior gap and the development of this relationship over time are required.

This paper reports on a study into the change in behavioral intention toward and actual engagement in e-cycling of participants of an e-cycling stimulation program. This study explores two specific aspects that give insights into the underlying mechanisms and should help policymakers in adjusting urban mobility programs to increase e-cycling. The first aspect is the longitudinal effect of the relationship between behavioral intention and behavioral change from car commuting to e-cycling in daily practice. Previous research has shown that participating in an e-cycling incentive program has positive effects on e-cycling, where travel distances and the number of e-cycling increase over time ((De Kruijf et al., 2018; Sun et al., 2020). In order to promote e-cycling, it is important to understand the mechanisms for overperformance or underperformance (relative to one's intentions) of participants and how often this occurs. Next, insights into how behavior by participants changes and how the intention-behavior consistency is adjusted over time during the program are important. In line with the Theory of Planned Behavior (TPB)(Ajzen, 1991) and the Extended Model of Goal-directed Behavior (EMGB)(Perugini and Conner, 2000), we assume that behavioral intentions are influenced by factors relating to one's beliefs, social influences, anticipated emotions, and perceived level of control. In addition, it has been documented that prior cycling behavior, spatial context, and personal and household characteristics impact e-cycling behavior. Therefore, we investigate how both sets of variables influence intention-behavior consistency.

The remainder of this paper is organized as follows. Section 2 reviews findings from other studies that were focused on behavioral modification. Section 3 describes the method and the data collection. Section 4 analyzes the results of the changes in intention and behavior. Section 5 concludes with the results of the research.

3.2 Literature review

3.2.1 Beliefs and behavioral change

Despite the many physical and mental health advantages and positive contributions to the environment that result from bicycle usage (Akar & Clifton, 2009; Sugiyama et al. 2008) a vast amount of people does not use the e-bike to commute to work. A comparison can be drawn to other physical activities such as healthy eating, maintaining a healthy weight, and giving up smoking, where changing behavior is favorable, but difficult to accomplish for many (Faries, 2016).

Behavioral changes related to transportation have been widely studied (Gärling & Fujii, 2009; Cairns et al., 2017; Fujii & Taniguchi, 2006). Because e-bike use in a cycling stimulation program can be regarded as part of a behavioral modification process, existing literature on travel behavior modification may provide insight into the reasons for enrollment in such a program. One often-used approach to the characteristics of the decision-makers and the decision-making process is the Theory of Planned Behavior (TPB)(Perugini and Conner, 2000). The TPB proposes that decisions about behavior (including travel) are driven by various personal beliefs: 1) beliefs about the outcome of the decision (attitudes), 2) beliefs about the norms held by oneself and others about the behavior, and 3) beliefs about the capabilities and inhibitions pertaining to the behavior (perceived behavioral control) (Ajzen, 1991). These beliefs determine, in combination, the intention to engage in the behavior, which logically influences whether the behavior is engaged in or not. For instance, Bamberg (2006) describes how a residential relocation combined with a public transport trial ticket leads to changes in attitudes, social norms, and perceived behavioral control, eventually leading to behavior change. Hunecke et al. (2001) describe how interventions aimed at influencing personal and social norms contribute to behavior change toward public transport. In the health domain, Hardeman et al. (2010) describe a series of interventions based on TPB, of which approximately two-thirds appeared to be successful. While the TPB is an important and relevant framework for understanding behavior change, there exist alternative behavioral frameworks that also provide starting points for behavior change interventions and intention-behavior inconsistency. According to these theories, the aim to increase affect and well-being during travel, or a state of (dis)satisfaction with the current travel behavior, could be triggers for behavioral change.

3.2.2 Affect, satisfaction, and behavioral change

Over the past decade, research on well-being has increasingly found its way into transportation research (Olsson et al., 2013; De Vos et al., 2018; De Vos et al. 2020; Van Wee & Ettema. 2016). Put briefly, it is assumed that the act of traveling has a direct impact on travelers' well-being, which involves both an affective (i.e., emotional) and a cognitive component. Various measurement tools have been developed to measure well-being during travel. Some scholars have used single-item cognitive scales (e.g., 'How satisfied were you with your trip' (Abou-Zeid and Ben-Akiva, 2012). In contrast, other scholars have used multiple affective items (Morris and Guerra, 2015) or a combination of affective and cognitive items (Ettema et al., 2011). In addition, well-being related to travel can be measured during or immediately following the trip, in retrospect, thinking back of a trip, or more generally concerning a trip type (such as commuting). Travel-related well-being varies consistently across modes. In general, the affective state associated with the private car is positive due to the easy access to out-of-home mundane activities (Bergstad et al., 2012), non-instrumental factors such as joy, independence, freedom, mastery, and prestige, and car travel as an enjoyable activity in itself. The private car is also attractive because it provides privacy and security (Gatersleben et al., 2014). Research by Novaco and Gonzales (2009) shows that, in contrast to the positive effects mentioned above, some car drivers experience high levels of stress and that long commute trips in congested traffic cause residual stress in the working place. Relative to other modes of transport, commuting by car is experienced worse than active commuting (walking and cycling) and about the same (Olsson et al., 2013) or slightly better than public transport (Ettema et al., 2010; Friman et al., 2013; Tommy Gärling & Friman, 2018). Travel satisfaction by slow modes such as cycling and walking is consistently found to be higher than travel satisfaction by automobile and public transport (Olsson et al., 2013; St-Louis et al., 2014; Gatersleben & Uzzell, 2007; Martin et al., 2014). While, in general, walking and cycling are reported as being favorable travel modes in terms of yielding the highest satisfaction scores, it is likely that environmental and personal factors influence the satisfaction with active travel. In reviewing environmental factors that stimulate cycling, Heinen et al. (Heinen et al., 2010) suggest that urban form (with implications for trip distances), network layout, mixed land use, quality and safety of infrastructure (including traffic lights and crossings and surface quality), aesthetics of the landscape, hilliness, weather, and season. With respect to environmental factors, it is found that the duration of trips by slow modes of transportation has negative impacts on travel satisfaction (St-Louis et al., 2014), likely attributed to fatigue effects.

The above indicates that the emphasis in existing studies has been on cross-sectional studies of how differences between travel modes and travel conditions lead to different levels of well-being during travel. However, scholars outside the transportation area suggest that affect may also be a driver of behavior change. Russell (2003) describes how individuals' affective state is a core driver of action, in the sense that they seek to move away from negative affective states (avoidance) and seek positive affective states (approach). In a similar vein, negative affective states associated with a certain current travel mode may trigger individuals to explore and use alternative ways of travel, leading to better affective outcomes.

Another indication of the relevance of affect related to current behavior is obtained from the Extended Model of Goal-directed Behavior (EMGB) (Perugini and Conner, 2000), which suggests that goal-perceived feasibility, goal desire, and goal-anticipated emotions, along with cognitive factors such as attitude, subjective norms, and perceived behavioral control from the TPB, are drivers of decisions about, e.g., environmental behaviors. This mechanism also suggests that negative affect associated with one choice outcome based on previous experiences, may lead to an increased likelihood of changing one's behavior. In transport marketing studies (Oliver, 1980) it has been found that satisfaction with a product or a service may influence the intention to consume the product a next time. Thus, both affective and cognitive assessment of prior experience may influence future intention and behavior, which can be regarded as loyalty to the product or service. Consequently, to keep e-cycling during an e-bike stimulation program may depend on both the affective and cognitive evaluation of the commute.

3.2.3 Intention-behavior gap

The situation where the transition from intentions to the actual behavioral change fails is called the intention-behavior gap. In socio-psychological models, intention is considered 'the most immediate and important predictor of a person's behavior' (Sheeran, 2005). It is, therefore, important to understand the mechanisms behind intention and behavioral change. In order to understand and moderate the intention-behavior gap, there has been much discourse on variables beyond the commonly assessed belief-related variables within the TPB (subjective norms, perceived behavioral control, and attitude) (Armitage & Conner, 2001; Ajzen, 1991). First, implementation intention or behavioral volitions as concretization of the intention have been added to the TPB as mediating variables between intention and behavior (Sniehotta et al., 2005 ; Reuter et al., 2008 ; Wieber et al., 2015). Second, past behavior or habit is added as important factor to underpin behavior in a specific context (Gardner, 2015; Gardner & Rebar, 2019). Third, goal-related variables are added such as goal perceived feasibility as evaluation to what extent the intended goal is likely to be achieved, and goal desire as degree to which one is willing to achieve the goal from the Model of Goal-directed behavior (EMGB) (Perugini and Conner, 2000) which relates to the concepts of self-efficacy and action control (e.g., self-monitoring, effort) (Sniehotta et al., 2005) found in other research. Also goal-anticipated emotions are added as variables, which also relate to people's personality (MacCann et al., 2014; Monds et al., 2016).

In line with the above insights, this study assumes that the relationship between intentions to e-bike and actual e-biking frequency is mediated by behavioral volition. In addition, we assume that the intention to e-bike is influenced by goal perceived feasibility, goal desire, and goal anticipated emotions (see Figure 1).

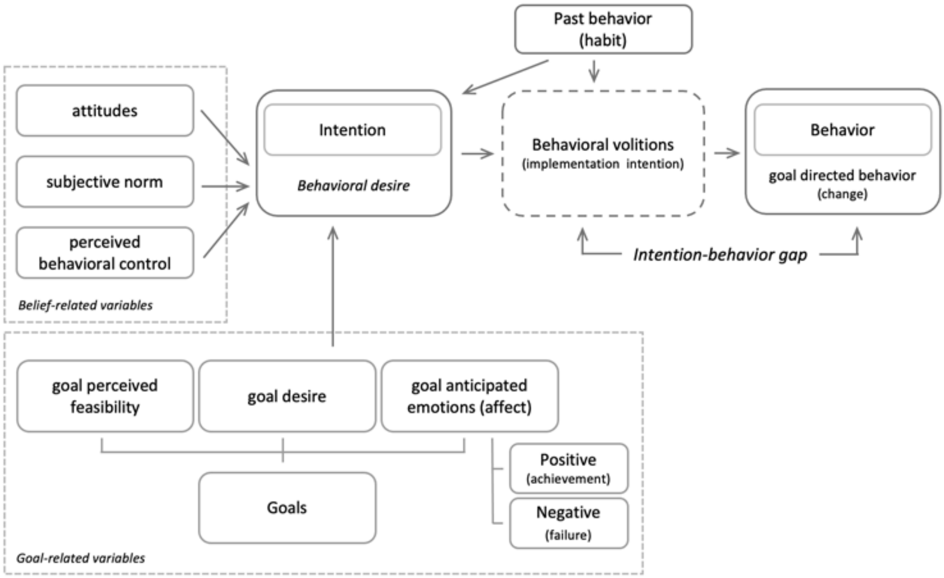

Figure 1. Conceptual framework

3.3 Methods

3.3.1 Study context

To actively stimulate the behavioral change from car commuting to e-cycling, the collaborating regional and local road authorities in the province of Noord-Brabant developed a large-scale e-cycling incentive program (B-Riders). With approximately one million inhabitants (40% of the total regional population) living between five and fifteen kilometers from the main working locations and economic centers (Figure 2), the long-term effects of the expected behavioral change were estimated to have a significant impact on the total regional modal split and reduction of congestion. The incentive program builds on previous projects in the Netherlands, in which participants received financial compensation upon changing their behavior in a more sustainable mode choice, such as the Spitsmijden (peak avoidance) project, which provided participants with financial compensation to travel out of the peak hours (Ben-Elia and Ettema, 2009).

The collaborative road authorities used a relatively new approach to stimulate behavioral change based on the actual e-cycling performance of participants instead of stimulating the purchase of regular e-bikes. All people working in Noord-Brabant were invited, via social media and regional newspapers, to participate for a year (twelve months) in a large-scale incentive program. Participants were allowed to make use of a regular e-bike or a speed pedelec, whereas in the practice of 2013, the number of speed pedelecs was limited. For this study, the behavior of all participants with a regular e-bike in the B-Riders program was monitored between September 2013 and September 2014. Online surveys were conducted to assess the development between the intended e-cycling and the actual behavioral change over time within the B-Riders program.

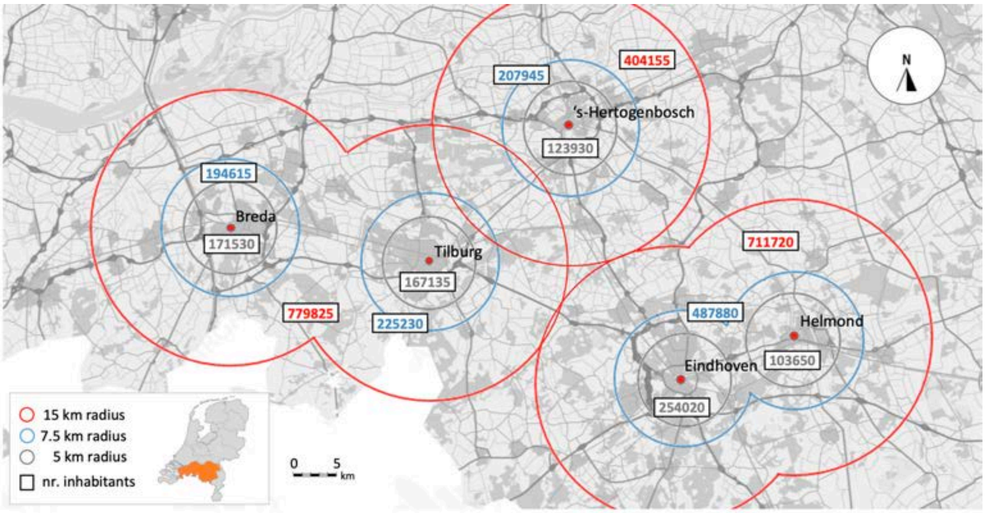

Figure 2. Situational overview of the Province of Noord-Brabant, with 5, 7.5, and 15 km radius from 5 main cities with the number of inhabitants per radius

3.3.1 Study design

Because the incentive program focused on behavioral change of car users to (e-)cycling, participants had to meet several recruitment conditions. First, all participants at least had to travel to work for a minimum of 50% to work by car and with a minimum commute distance of three kilometers. The minimum share of working days per week by car was set this way due to the relatively new approach and the uncertainty about the number of participants willing to enroll in the program. Second, participants had to be between eighteen and sixty-five years of age (the retirement age at that time) with a working location within the province of Noord-Brabant. Finally, all participants agreed to actively participate in the study by filling out three questionnaires throughout the experiment.

With the overarching program objective to reduce regional peak hour car congestion, participants received a €0.15 compensation per kilometer cycling during the morning and evening peak hours. Additionally, a compensation of €0.08 per kilometer at other times was set to make the program more appealing and encourage e-cycling for other purposes for trips. During the twelve months participation period, the total financial incentive per participant was capped at €1,000 (one thousand euros). Based on a 10-kilometer average commuting distance, it would take participants approximately a year to reach this maximum financial compensation. Within the duration of the program, 25 participants reached the maximum financial incentive. In total, €1,000,000 (one million euros) was paid out to participants based on their performance. After finishing the program, the calculated effect was that more than one million trips by car during peak hours were avoided.

3.3.2 Longitudinal setup

To assess the behavioral change during the program, a series of three questionnaires were administered via the internet. At the start of participation in the program, a baseline questionnaire (T0) was conducted, where participants had to report the number of days using their habitual travel mode(s) for commuting in an average working week before entering the incentive program. The options in the baseline questionnaire for the main mode of transport were car, carpool, motor, bus, tram, metro, moped/scooter, bicycle, and walking. Next, participants reported their behavioral intention to e-cycle to work expressed as the frequency in days of the week choosing the e-bike. In addition, participants reported on a series of constructs derived from the EMGB and TPB models, using established measurement scales, which is further explained below. Furthermore, questions were included to measure relevant personal and household characteristics, spatial characteristics, and work-related circumstances, which were suggested in previous e-cycling research (De Kruijf et al., 2018; Fishman & Cherry, 2016; Heinen et al., 2010; Plazier et al., 2017). Finally, as past behavior of people has frequently been demonstrated to predict changed behavior better than measures of intention and attitude (e.g. Bentler & Speckart, 1979; Verplanken & Aarts, 1999; Verplanken & Van Knippenberget al., 1997), participants were asked to report on their habitual travel behavior.

A second questionnaire (T1) was conducted one month after the starting date of all individual participants, where groups of participants started in batches at different start dates due to the organization of the program. Participants were invited to report again on the frequency of days using the main modes of transport for commuting in a working week over the last month, where e-cycling was added. Similar to the baseline questionnaire, the behavioral intention for e-cycling in the number of days a week in an average week for the next period was asked together with all EMGB variables.

During the third and final questionnaires, which were conducted on each individual participant after six months of participation in the program, participants were asked again to report the intention of their commuting behavior in the number of days commuting by the different main modes of transport in an average week in the past period.

Of all 732 participants completing the first survey at the start of the program, 692 participants (a decrease of 5,5%) also completed the questionnaire at T2, and finally, with another decrease of 11,3%, a total of 614 participants completed the questionnaire at T3. In absolute number, the decrease in men (-47 participants) was less than in the female group (-71 participants) between T1 and T3. This study is eventually based on longitudinal responses from 547 participants after cleaning the survey for incomplete data.

3.3.3 Questionnaire development

Personal, household, and spatial characteristics

In addition, the questionnaire asked participants a set of questions about personal and household characteristics, including gender, age, educational level, income, car ownership, household composition, and subjective health status. The urbanization level for each participant was derived from each participant's home location postal code. Combined with the postal code of the working location, the e-bike distance was determined using the GIS (Geographical Information System) fastest path analysis based on the Open Street Map cycling network.

Intention-related determinants

In order to investigate behavioral intention, participants were questioned about their expected commuting trips during the incentive program in the next month. Therefore, the goal-related variables (perceived goal feasibility, goal desire, and goal-anticipated emotions) from the EMGB were used to measure intention, along with belief-related variables (attitude, perceived behavioral control, and subjective norms) from the TPB. In the EMGB section of the questionnaire, the goal behavior was defined as 'making use of the e-bike to go to work'. Next, all participants were asked to report the expected number of days a week to travel to work by e-bike in that period as their behavioral volition. Based on this behavioral volition or implementation-intention, participants reported on all nine EMGB (Perugini and Conner, 2000) determinants divided into the next main aspects: attitude, subjective norm, perceived behavioral control, past behavior, goal-perceived feasibility, goal desire, and goal-anticipated emotions (affect), where the latter is sub-divided into positive (achievement) and negative (failure) affect. Participants were asked to report on a seven-point Likert scale ranging from very unlikely (1= very unlikely) to very likely (7= very likely).

3.3.4 Sample demographic information

Based on e-cycling research showing that participants already making use of a conventional bicycle to commute to work exhibited different behavioral changes within an incentive program, participants were divided into car-commuters and multimodal car-commuters. The division between the two groups is based on their self-reported share of regular cycling commuting days in an average week. Car-commuters are the ones who never use the regular bicycle to travel to work in the baseline situation. Multimodal car-commuters reported (T0) to use different modes of transport to commute with a range of days using the regular bicycle. Table 1 specifies the total sample characteristics, including urbanization and the habitual cycling proportion before commuting by e-bike of all participants, car-commuters, and the multimodal car-commuters.

Table 1. Sample composition of all (547) participants; (295) unimodal car-commuter and (252) multimodal car-commuters (in %)

Variable	Category	Total	Car	Multimodal
Age	25 - 39 years old	12.07	14.24	9.52
	40 - 49 years old	36.38	35.93	36.90
	50 - 65 years old	51.55	49.83	53.57
Gender	Male	48.45	44.07	53.57
	Female	51.55	55.93	46.43
Education level	Lower education | primary and secondary	15.49	16.27	16.26
	Vocational education	27.61	26.10	28.86
	Higher education | (applied) scientific	56.90	57.63	54.88
Self-reported physical condition	Bad	13.39	15.36	11.11
	Neutral	18.53	19.11	17.86
	Good	33.03	34.47	31.35
	Excellent	35.05	31.06	39.68
Car ownership	1 car	49.73	47.46	52.38
	2+ cars	50.27	52.54	47.62
Net household income (in € per month)	< 3,000	42.92	42.98	42.86
	3,000 to < 4,000	37.30	39.57	34.76
	> 4,000	19.78	17.45	22.38
Household com-position	Single	6.58	8.81	3.97
	Single parent	2.19	2.37	1.98
	Couple without children at home	34.92	34.24	35.71
	Couple with children at home	56.31	54.58	58.33
Urbanization level at home postal code	Highly urbanized	14.99	13.22	17.06
	Moderate urbanized	22.67	22.03	23.41
	Less urbanized	31.99	31.19	32.94
	Not urbanized	30.35	33.56	26.59
Cycle distance	0 - 5 km	3.66	1.69	5.95
	5<10 km	19.20	10.51	29.37
	10<15 km	30.53	32.20	28.57
	15<20 km	28.52	31.53	25.00
	20+ km	18.10	24.07	11.11
Flexibility working hours	Yes	59.78	58.98	60.71
	No	40.22	41.02	39.29

Table 1 shows that nearly half of the participants are between 50 and 65 years old and most have a university or higher vocational degree. This is consistent with the publications at the time of data collection reporting that the e-bike is especially popular in older cohorts and among higher educated segments (Fishman and Cherry, 2016; (Johnson & Rose, 2013). More than 50% of the participants belonged to the category "couple with children living at home." Half of the sample (50.27%) owned at least two cars, and most participants (57.08%) were in the mid- to high-income categories (>3,000 euro/month). Additionally, 77.15% of the participants had a cycle-commute distance of more than 10 kilometers, suggesting that the e-bike may be an important alternative to car-commuting, which also offers acceptable travel times for longer distances. Finally, 59.78% of the sample had flexible working hours.

The subdivision of all participants shows that the share of women within the unimodal car commuters' group (55.93%) is higher compared to (46.43%) in the multimodal car commuters group. The share of car ownership with two or more cars per household in the unimodal car-commuters group (52.54%) is higher than the 47.62% in the group of multimodal car commuters. Finally, the share of participants with cycle-commute distances of more than 10 kilometers is 87.81% for the unimodal car-commuters group compared to 64.68% for the multimodal car-commuters group.

3.3.4 Analytical approach

To explore the intentional and behavioral effects caused by the program, we conducted two descriptive analyses: one on the changes in behavioral intention between the start of the program and during participation, and one on the differences between intention and the actual behavior over the duration of the program. As regular cycling experience might have a different effect on intention and behavior between car commuters with and without the subdivision was added to the analyses.

In order to analyze the factors influencing the changes in intention, behavior, and the combination of both, we conducted ordinal logistic regression analyses. Therefore, we calculated the changes in intention of the number of days of e-cycling to the workplace between the situation after a month of participation (T1) and baseline (T0), where the outcome varies between an increase, no change, and a decrease. The same calculation was performed on the actual change in the number of days of e-cycling to the workplace between the situation after half a year of participation (T20) and the situation after a month of participation (T1). The outcome also varies between an increase, no change, and a decrease in days per week. Next to the EMGB variables, we incorporated personal, household, and commute characteristics as explanatory variables. This allows us to draw conclusions about the factors that stimulate a positive response to the e-bike incentive program.

3.4 Results

3.4.1 Descriptive analyses

To address the longitudinal effect on intention-behavior consistency, Table 2 shows the relation between the reported e-cycling behavior and the intended number of working days using the e-bike to commute. The overview shows the difference between the stated intentions prior to the experiment and the actual behavior after a period of participation. The table describes the relationship between a) the stated intention (T0) and behavior

(T1) and b) the intention (T1) and behavior (T2), expressed as the number of participants. Additionally, the shares of underperformance (less), overperformance (more), and corresponding intention-behavior (equal) were added.

First, comparing the stated e-cycling intention at the baseline and the actual behavior after one month of participation shows that 51% of all participants have an intention-behavior consistency and do what they intended in the first month of participation. The group of participants who intended to use the e-bike five or more days a week showed the lowest intention-behavior consistency with 37%. It is notable that there is actually a small group of participants who do not have an intention (anymore) to e-cycle to work. All other groups show between 47% and 57% intention-behavior consistency, where the majority of inconsistent participants are using the e-bike less than the intended number of days with 29%-41% underperformance. Next to the general overview of all participants, Table 2 shows the difference between unimodal car-commuters and multimodal car-commuters. With a comparable number of participants in both groups, the overall average in similarity between baseline intention and e-cycling after a month higher for the multimodal commuters (55%) than the unimodal car-commuters (48%). The difference between the two groups is mostly in the limited number of multimodal participants overperforming. This can be understood from the habitual cycling experience of the group already commuting on the regular bicycle for some days in the week. Possibly, they are better able to envision what a specific e-biking frequency entails, so that it meets their expectations and they maintain their e-biking level.

Table 2. Overall e-cycling intention-behavior consistency, unimodal and multimodal car-commuters

E-Cycle Intention T0	Difference in e-cycling behavior T1 vs. intention T0										Difference in e-cycling behavior T2 vs. intention T1									
Total Group	never	1 day	2 days	3 days	4 days	5+ days	Sum	Less	Equal	More	never	1 day	2 days	3 days	4 days	5+ days	Sum	Less	Equal	More
0 workdays a week	**4**	2	1	0	0	0	7	-	57%	43%	**1**	5	0	2	1	1	10	0%	10%	90%
1 workday a week	6	**9**	3	0	0	1	19	32%	47%	21%	4	**12**	12	4	1	1	34	12%	35%	53%
2 workdays a week	3	21	**46**	12	2	0	84	29%	55%	17%	4	11	**38**	33	4	2	92	16%	41%	42%
3 workdays a week	4	10	46	**85**	19	1	165	36%	52%	12%	2	12	24	**82**	28	5	153	25%	54%	22%
4 workdays a week	1	2	8	59	**95**	5	170	41%	56%	3%	3	4	3	39	**99**	16	164	30%	60%	10%
5+ workdays a week	1	0	2	12	49	**38**	102	63%	37%	0%	2	0	1	11	36	**44**	94	53%	47%	0%
	3%	8%	19%	31%	30%	8%	547	41%	51%	8%	3%	8%	14%	31%	31%	13%	547	29%	50%	21%
Car-com-muters	never	1 day	2 days	3 days	4 days	5+ days	Sum	Less	Equal	More	never	1 day	2 days	3 days	4 days	5+ days	Sum	Less	Equal	More
0 workdays a week	**4**	2	1	0	0	0	7	-	57%	43%	**1**	3	0	2	0	1	7	0%	14%	86%
1 workday a week	5	**8**	2	0	0	0	15	33%	53%	13%	4	**8**	11	2	1	1	27	15%	30%	56%
2 workdays a week	3	17	**30**	12	2	0	64	31%	47%	22%	4	9	**27**	21	4	2	67	19%	40%	40%
3 workdays a week	2	7	28	**46**	13	1	97	38%	47%	14%	2	8	16	**47**	10	2	85	31%	55%	14%
4 workdays a week	1	2	3	29	**34**	2	71	49%	48%	3%	1	3	2	23	**37**	6	72	40%	51%	8%
5+ workdays a week	0	0	1	6	18	**16**	41	61%	39%	0%	0	0	1	6	14	**16**	37	57%	43%	0%
	5%	12%	22%	32%	23%	6%	295	41%	47%	12%	4%	11%	19%	34%	22%	9%	295	32%	46%	22%
Multimodal commuters	never	1 day	2 days	3 days	4 days	5+ days	Sum	Less	Equal	More	never	1 day	2 days	3 days	4 days	5+ days	Sum	Less	Equal	More
0 workdays a week	**0**	0	0	0	0	0	0	-	-	-	**0**	2	0	0	1	0	3	-	-	-
1 workday a week	1	**1**	1	0	0	1	4	25%	25%	50%	0	**4**	1	2	0	0	7	0%	57%	43%
2 workdays a week	0	4	**16**	0	0	0	20	20%	80%	0%	0	2	**11**	12	0	0	25	8%	44%	48%
3 workdays a week	2	3	18	**39**	6	0	68	34%	57%	9%	0	4	8	**35**	18	3	68	18%	51%	31%
4 workdays a week	0	0	5	30	**61**	3	99	35%	62%	3%	2	1	1	16	**62**	10	92	22%	67%	11%
5+ workdays a week	1	0	1	6	31	**22**	61	64%	36%	0%	2	0	0	5	22	**28**	57	51%	49%	0%
	2%	3%	16%	30%	39%	10%	252	40%	55%	4%	2%	5%	8%	28%	41%	16%	252	25%	56%	19%

Second, the difference between the stated e-cycling intention and actual e-cycling frequency one month and six months after the start of participation shows a comparable intention-behavior consistency of 50% on average. However, the shares of underperforming (less) and overperforming (more) are more balanced at T2 than at T1, where the group overperforming increased. This suggests that participants have had to get used to using the e-bike to travel to work. Maybe not surprisingly, the groups with the intention of e-cycling one of two days in the week showed overperformance of 53% and 42%, respectively. Most participants of these groups take the e-bike one more day than intended. The group of participants who intended to use the e-bike four to five days per week showed high consistency (47%-60%), and when they differ, participants tend to only e-cycle one day less than intended. With comparable shares, both the group of unimodal and multimodal car-commuters show hardly changed intention-behavior consistency during participation. Both groups show a similar relative increase in overperformance in the second period.

To address the development of e-cycling intention, Table 3 shows the changes in behavioral intention by participants between T1 and the start of the program (T0). It may be assumed that expectations and intentions are more realistic after a month of participation in the program. A subdivision is presented, where participants were asked to indicate their use of the regular bicycle at T0. Given the Dutch context, one might assume that all participants in the program are capable of cycling in general but not all use the bike to go to work.

Table 3. Relationship between baseline use of regular bike and e-cycling intentions, unimodal and multimodal car-commuters

	Difference in e-cycling Intention T1 vs. T0 (divided in regular cycling experience)											
Use of the regular bike T0	-4 days	-3 days	-2 days	-1 day	equal	+1 day	+ 2 days	+ 3 days	Sum	Less	Equal	More
0 workdays a week	3	2	9	48	192	32	9	0	295	21%	65%	14%
1 workday a week	0	2	4	21	56	6	0	0	89	30%	63%	7%
2 workdays a week	1	0	0	12	64	5	0	1	83	16%	77%	7%
3 workdays a week	0	0	0	4	28	7	0	0	39	10%	72%	18%
4 workdays a week	0	0	0	3	24	2	0	0	29	10%	83%	7%
5+ workdays a week	0	0	1	1	10	0	0	0	12	17%	83%	0%
Total	4	4	14	89	374	52	9	1	547	20%	68%	11%
	1%	1%	3%	16%	68%	10%	2%	0%				

Overall, 68% of all participants did not change their intention over the duration of the program. The subdivision in self-reported regular cycling (T0) frequencies shows an increasing percentage of participants in the category ‘equal’. Participants who reported a regular cycling frequency of zero days a week consisted of people who did not use the regular bicycle at all (unimodal car-commuters), together with people who used the regular bicycle irregularly and less than one day a week on average. Participants within the group of unimodal car-commuters show a 65% similarity in intention after one and six months. Of the remaining participants, 14% adjusted their intention positively to more e-bike commuting and 21% negatively, where most of these latter people adjusted their intention to one day a week.

The group of participants with one day a week of regular bicycle use shows an almost similar share in equal intentions of 63%. In comparison to the group without cycling commute habits with the regular bicycle (T0) only 7% adjusted their intention to e-bike more. This could be explained by their already developed (regular) cycling experience to work. The group of participants with two and three days of regular cycling behavior shows 72% to 77% of unchanged intention. The day-to-day cyclists with four or five days of regular cycling a week at the start of the program show a consistency of 83% in behavioral intention, which again can be explained by the experience in the past with regular cycling to work. From this group, most participants who changed, lower the intention, but not consistently with original cycling frequencies.

3.4.2 Regression models of e-bike intention and behavior

To investigate how both e-cycling intention and intention-behavior change over time, ordinal regression analyses were conducted in two models.

1. E-cycling intention T0 vs. behavior T1: model 1
2. E-cycling intention T1 vs. behavior T2: Model 2

The dependent variable per model is defined as the difference between actual and intended e-cycling frequency, where the outcome can be (1) overperformance, where the actual number of e-cycling days is more than intended, (2) a consistent situation, or (3) underperformance where the actual number of e-cycling days is less than intended.

As outlined in our conceptual framework, we hypothesize that goal-related variables, as defined in the EMGB and TPB, influence e-cycling intention and behavior (Dijst et al., 2008), we used goal desire, positive and negative anticipated emotions, past conventional cycling behavior, attitude, subjective norms, perceived behavior control and behavioral intention as independent variables. Moreover, independent variables like personal (gender, age, health status), household characteristics (household income, education, household composition, urbanization level, car ownership), and cycling commute distances were included. Table 4 shows the results of the two models.

In general, the goal-related variables do not show many structural significant relations throughout the models. Only a few variables have an impact on the changes in intention and behavior. Looking at the intention-behavior consistency (model 1), there is no significant relationship between the belief and goal-related variables. It might be speculated that intention-behavior consistency is a different process from the development of intention or behavior itself. The actual behavior might be determined by more practical factors, including preparation (putting on rain gear, getting the e-bike out of the shed), working conditions, and feedback from peers, among others. In the first month of participation, the group between 25 and 39 years old used the e-bike systematically less than intended (-0.644), less than people with an age over 50 years. Singles also are more likely to e-cycle less (-0.940) than intended in the first month. On the contrary, having one car available in the household only increases (0.393) e-cycling in the first month relative to their intention. Finally, in the cycling distances up to 10 kilometers, commuting participants significantly underperform (0 to 5 km. = -1.090 and 5 to 10 km. = -0.584) compared to the intended number of e-cycling days. It might be speculated that participants with a longer commuting distance have a stronger commitment or better preparation because of the impact of the related travel time.

In the second period, between a month and half a year after starting the program (model 2), the negative anticipated emotion of guilt (not achieving the goal) affects the consistency, where participants with anticipated guilt are more likely to underperform relative to their intention (-0.158). The perceived ease of using the e-bike affects intention-behavior consistency in e-cycling (0.232) in a positive way. Finally, male employees tend to significantly e-cycle less (-0.485) than intended in the second stage of the program. Notably, the physical condition of participants, urbanization level, income, and household composition do not significantly impact changes in intention-behavior consistency.

The model fitting data show the significance of the improvement of fit between the intercept-only model and the full model. The non-significant models are indicators that the models fit the data well (Petrucci, 2009). Despite the significance, the models can be used to evaluate the direction of effects.

Table 4. Ordinal regression analysis of intention-behavior consistency

			Model 1 Intention T0 vs. Behavior T1	Model 2 Intention T1 vs. Behavior T2
	minimum (1)	maximum (7)	Estimate	Estimate
Goal desire	very weak	very strong	0.035	-0.241
	strongly disagree	strongly agree	-0.039	-0.070
Positive anticipated emotions	excited	not excited	0.108	-0.168
	delighted	not delighted	-0.145	0.357
	happy	not happy	-0.077	-0.259
	satisfied	not satisfied	0.078	-0.024
	proud	not proud	-0.017	-0.053
Negative anticipated emotions	angry	not angry	-0.086	-0.030
	frustrated	not frustrated	0.043	0.066
	guilty	not guilty	-0.068	-0.158 *
	sad	not sad	0.054	0.029
	disappointed	not disappointed	0.059	0.071
	worried	not worried	0.119	0.024
	uncomfortable	not uncomfortable	-0.035	0.035
Past behaviour			-0.066	-
Attitude	useless	useful	-0.114	-0.164
	Ineffective	Effective	0.232	0.031
	expensive	cheap	-0.104	-0.139
	unpleasant	pleasant	0.063	0.014
	unattractive	attractive	0.303	-0.254
	unenjoyable	enjoyable	-0.314	-0.044
Subjective norms	people who are important to me, think I should/should not…		0.046	-0.100
	people who are important to me would (dis) apporve		0.091	0.112
	people who are important to me do not care whether I choose		0.014	-0.085
Perceived behavioral control	e-cycle n amount of days to work		0.082	-0.023
	if I wanted to, it would be easy to….		0.034	0.232 *
	it is entirely up to me		0.121	-0.117
	I'm confident that I would use …		-0.034	-0.097
Behavioral intention	my desire to choose is …		-0.019	0.213
	I intend to choose ….		-0.105	0.058
	I gave it a good thought how I could use ….		0.115	-0.049
Age	25-39 years old		-0.644 *	-0.208
	40-49 years old		-0.408	-0.053
	50+ years old		-	-
Gender	male		-0.343	-0.485 *
	female		-	-
Physical condition	bad		0.091	-0.051
	neutral		-0.015	-0.267
	good		-0.125	0.011
	excellent		-	-
Car ownership	1 car		0.393 *	0.178
	2+ cars		-	-
Household income (in € per month)	< 3.000		-0.419	-0.289
	3.000 - < 4.000		-0.197	-0.387
	> 4.000		-	-
Household composition	Single		-0.940 *	-0.452
	Single parent		-0.654	0.965
	Couple without children		-0.172	-0.033
	Couple with children		-	-
Residence urbanization	(very) strong Urbanized		-0.009	-0.102
	moderate urbanized		-0.290	-0.327
	Less urbanized		0.041	0.086
	Not urbanized		-	-
Cycle Distance (per commute trip)	0-5 km		-1.090 *	-0.730
	5<10 km		-0.5840 *	0.193
	10<15 km		-0.466	0.031
	15<20 km		0.039	0.287
	20+ km		-	-
Cycling Share	T0_CycleShare		0.327	-0.350
	Model fitting		0.352	0.004 *
	Goodness of fit	Pearson	0.076	0.207
		Deviance	0.985	0.442

3.5 Conclusion and discussion

This study reported on the relation between the e-cycling intention and actual behavioral change within a large-scale e-cycling incentive program in the Netherlands, specifically in the province of Noord-Brabant. The main objective of the program was to incentivize car-commuters to use e-bikes in daily commuting as an alternative to car-commuting that causes congestion in the vicinity of the cities. For each kilometer commuted by e-bike, participants in the program earned monetary incentives. The incentive program was a collaboration of the national government, regional government, and the main cities aiming to reduce car commuting with target numbers on avoiding car commuting in peak hours. With a longitudinal design based on surveys, this study observed the changes in e-cycling intention and the actual behavioral changes in order to understand the underlying mechanisms of behavioral change over time. Research on e-cycling has already shown that because of the electric peddle support of the e-bike, restrictions on range and physical effort are mitigated, as the main barriers to conventional bicycle use in daily commuting (Heinen et al., 2010; Heinen and Handy, 2012).

Our study showed that the intention to e-cycle in daily commuting is quite constant over a period of a month, with two-thirds of all participants reporting the same intention at the start of the program as after a month of participation. One-fifth of all participants decreased their stated intention after the first month of experience, but most of them only reduced e-cycling intention by one day a week. Especially in the groups of participants with more days a week of conventional cycling experience, the changes in intention are less frequent, which might be explained by the habitual commuter-cycling experience. With respect to intention-behavior consistency, a distinction can be made between the experienced cyclists and participants without any or hardly any (one day a week) commuter-cycling experience (Gatersleben and Appleton, 2007). Comparing the e-cycling intention at the start of participation in the program to the behavior after a month shows that only half of the participants exactly meet their intention in the number of e-cycling days a week. Especially in the group of participants without conventional cycling experience for commuting, the use of the e-bike compared to their intention was higher, which might be explained by a very positive experience and satisfaction with their trip (de Kruijf et al., 2019). In the second stage (between a month and half a year of participation), the group with conventional cycling experience also more often showed an increase in e-cycling compared to the intention. The duration of the program to incorporate habituation is an important factor, while behavioral modification and adaptation take time. Overall, it can be concluded that a strong intention-behavior gap is not observed in the context of the e-cycling stimulation program. Most participants use the e-bike at least with the intended frequency or only slightly less. One explanation may be that the experience with e-cycling is positive and contributes to adherence to e-cycling. Another explanation is that enrollment in the program creates a strong incentive to continue e-cycling. In particular, the rewards per trip, needed to earn back the investment made in an e-bike may provide a strong incentive. Despite the limited overall significance, factors such as a relative young age, single car ownership, and living in a one person household significantly influence the intention-behavior consistency.

A question that remains is to what extent the effects on behavioral change by the incentive program are scalable to future incentive programs. The comparison was drawn between e-cycling and other favorite physical activities such as maintaining weight, healthy eating, and not smoking, which are challenging goals to accomplish (Faries, 2016). When the translation from intention to action fails, there is an intention-behavior gap. This study did not show convincing relations with belief-related variables as specified in the TPB and additional goal-related variables specified in the EMGB. It can be concluded that there are differences in intention-behavior consistency within the sample, which are, however, not directly related to the theoretical concepts of the TPB or EMGB. First, it can be argued if cycling to work is not that difficult in the Dutch context with its high-quality cycling infrastructure, positive cycling culture, and general cycling experience in society. Second, the monetary compensation within the program is introduced as an extrinsic incentive to motivate people to change their behavior. Participants in the program already had a positive mindset toward e-cycling and participating in an incentive program. One of the open questions still is how less motivated people can be persuaded to join such incentive programs. Third, participants can be influenced by outside pressure (Deci and Ryan, 1985). In that particular case, participants would feel pressured by people being important to them to show certain desired behaviors or be negatively influenced by the image of the e-bike as bicycle for the elderly only (Fishman and Cherry, 2016). The results do not show a significant relationship between the changes in intention or behavior, and outside pressure. It can be hypothesized that a specific group in society enrolled in the incentive program, which is less sensitive for negative outside pressure to demotivate people from participation. Because participants have already signed up voluntarily for the incentive program, the degree of self-selection of participants in the program can be questioned. Also, the initial purchase of an e-bike is expensive compared to a regular bicycle, which could have been a restriction for lower income groups in society to enroll. In addition, the sales and use of e-bikes increased in the Netherlands over the last couple of years, (38% between May 2019 and 2020)(BOVAG, 2020) which indicates an improvement of the image of the e-bike. Therefore, the question remains how to stimulate e-bike use among a wider audience to enroll in such an incentive program.

The question can be raised to what extent the results of the present study can be used to strengthen current (Dutch) cycling policies. From a policy perspective, the e-cycling incentive program is regarded as successful because the majority of participants intended, started, and persevered using the e-bike for one or more days a week to commute as an alternative to car-commuting. However, the question remains how people underperforming to their implementation intention can be stimulated to take up e-cycling more, as no clear indications have been found on the intention–behavior gap to enhance such an e-cycling incentive program.

Nevertheless, although it is likely that not all commuters will fully switch to using e-bikes in all weather conditions, a vast amount of car-commuting trips can be substituted with effective cycling policy measures (de Kruijf et al., 2018). Overall, the results indicate that e-bikes have a clear potential to substitute car use on commute trips. It is to be noted that over the last couple of years, regional policymakers in the Netherlands decided to decrease involvement in e-cycling incentive programs in general and particularly in monetary incentives. By shifting responsibility and facilities (increase in tax-related opportunities in facilitating the purchase of an e-bike) to employers, e-cycling is increasingly embedded in the mix of sustainable modal choices for employees. This studies shows that actively stimulating-bike use over time helps to sustain behavioral change towards e-bike use.

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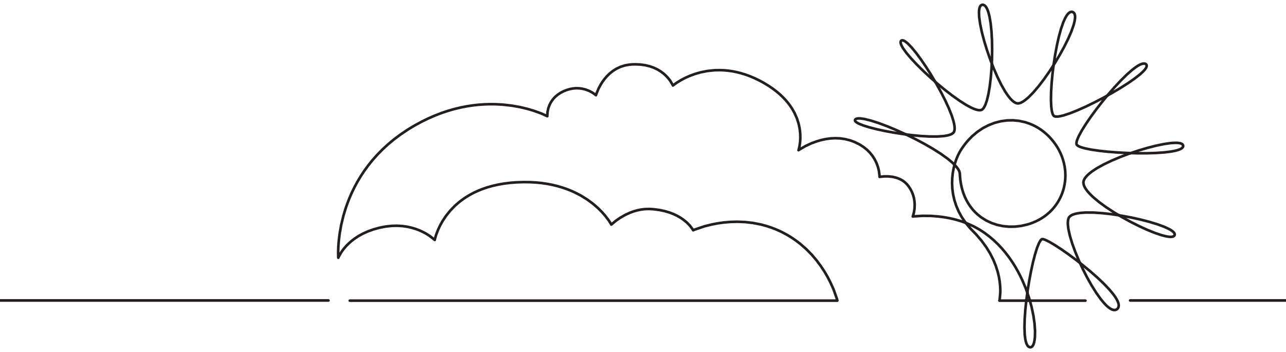
CHAPTER 4

Integrated weather effects on e-cycling in daily commuting: A longitudinal evaluation of weather effects on e-cycling in the Netherlands



Abstract

While in many regions the conventional bicycle has already been regarded as an environmentally friendly and healthy alternative to the car for daily commuting, societal and policy agendas are also increasingly promoting e-bike adoption. Adding to recent research on e-bike safety, satisfaction with travel and behavioral change, this paper reports on the impact of weather circumstances on the use of the e-bike in daily commuting in an e-cycling incentive program in the province of Noord-Brabant, the Netherlands. The impact of this incentive program was analyzed using a longitudinal design, and it combined travel patterns that were derived from individuals' GPS data over nine months, hourly observed meteorological data, and questionnaires on intended behavior and sociodemographic characteristics. The findings suggest that the presence of snow and ice, total precipitation, and high windspeed negatively affected the choice of commuting to work by e-bike, in this decreasing order of impact. Although the overall impact of air temperature on e-cycling was positive, the likeliness to commute by e-bike decreased at higher air temperatures. E-cycling under specific weather conditions was more likely if participants' intention to e-cycle under such weather conditions was stronger. Our study indicates that the benefits of the e- bike in daily commuting are underestimated in relation to adverse weather conditions. Respondents from households with one car only, therefore, have fewer alternatives in poor weather conditions: for these individuals, only total precipitation and the presence of relatively low air temperature impact e-cycling. In addition, reported gender and high wind speeds might have been expected to influence participation in e-cycling.

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4.1 Introduction

Over the last decades, cycling has become increasingly regarded as an environmentally friendly alternative to car trips for short distances. With increasing concerns about the environmental impact of car traffic, health, and livability, many cities are showing increasing interest in promoting the use of the bicycle as a part of the total urban transportation system (Fishman and Cherry, 2016; Handy et al., 2014; Pucher and Buehler, 2012). Regardless of health and environmental benefits related to conventional cycling (c-bikes) for short trips, many travelers choose to use other forms of transportation. Particularly for commuting to work, extensive research has revealed that distance, the built and natural environment, socio-economic factors, psychological factors, and an individual's physical condition may prevent people from commuting using c-bikes (Heinen et al., 2010; Heinen and Handy, 2012; Vandenbulcke et al., 2009; Gatersleben and Appleton, 2007; (MacArthur et al., 2014). Next to these personal and context specific circumstances, bicycle ownership and/or the presence of bike-sharing schemes also influence bicycle use. Although differences in personal factors such as gender and age have not been shown to have a distinctive influence on the likeliness to use shared bicycles, time of day and day of the week, as well as trip purpose have been found to be significantly different across users (Noland et al., 2016; Zhao et al., 2015). With the introduction of the electric peddle supported bicycle (e-bike), new opportunities have occurred where range (distance) and physical effort become less of a barrier compared to the c-bike.

In recent years, the substitution effect of e-bikes has gained increasing attention in research (Fishman and Cherry, 2016). Although several studies provide insights into the adoption of the e-bike and the reduction in trips made by competing modes of transport, information on the specific factors influencing e-cycling is limited. In general, the modal shift to e-cycling is affected by the availability of alternative modes of transport in the specific local context (Kroesen, 2017), the presence of bicycle infrastructure, and the existing cycling levels within a given area (Haustein and Møller, 2016). The shift from c-bikes towards the use of e-bikes has been prominent over the last decade in the Netherlands and Denmark, where cycling has already been common practice for a longer time (Sun et al., 2020; Fishman and Cherry, 2016). In areas with less established cycling cultures, but where public transport is more dominant, notably in many Chinese cities, the recent shift to e-bike usage came at the cost of using public transport, particularly buses (Cherry et al., 2016; Cherry and Cervero, 2007; Kroesen, 2017). In car-dominant areas like many North American and Australian cities where cycling is often still considered to be a fringe activity, e-bikes are substituted more frequently for car travel (Johnson and Rose, 2013; MacArthur et al., 2014; Popovich et al., 2014).

Existing research in the Dutch context on the degree of e-bike substitution and initial mode of transport seems to be inconsistent (Lee et al., 2015; Kroesen, 2017; Plazier et al., 2017; de Kruijf et al., 2018; Sun et al., 2020) because of differences in the availability of, and experience with, alternative modes of transportation, the local context, and the possibility of participating in incentive programs. However, research has shown that the use of e-bikes is influenced by gender, physical condition, car ownership, and household composition, and it has a positive impact on travel satisfaction in daily commuting for short and mid-range distances (de Kruijf et al., 2018). Limitations in range (as a result of the slower speed) and physical effort as a constraint of c-bikes are decreased by the introduction of the e-bikes (de Kruijf et al., 2018; Sun et al., 2020). Many Dutch regions have become aware over the last decade of the technical benefits associated with the e-bike and have accordingly developed cycling policies which emphasize high quality, safe regional cycling routes catering to the mid-range (7.5 - 15 km) cycling trip distances, which is highly relevant for commuting. In addition, they initiate e-cycling incentive programs aimed to engage employers and employees to reduce mental and monetary barriers to e-bike adoption. These policies have contributed to the increasing popularity of the e-bike among all age groups, with 18% of all cycling trips being made by e-bike (KiM, 2018).

Other factors that influence the attractiveness of c-bike commuting are the weather and climatic conditions (Rodríguez and Joo, 2004; Heinen et al., 2010), and several studies have suggested that weather conditions and cycling are strongly and closely linked (Nankervis, 1999; Corcoran et al., 2014). Several studies have demonstrated the effects of daily weather and climatic conditions on a wide range of travel behavior, including transportation mode choice and trip generation (Sabir et al., 2010; Böcker et al., 2013; Creemers et al., 2015; Liu et al., 2015). Especially for active modes such as walking and cycling, inclement weather conditions have a negative impact (more than other modes of travel) because of the exposure to the elements (Nahal and Mitra, 2018). As might be expected, commuters have been shown to be less sensitive to weather changes, compared to non-commuters. For example, poor visibility and heavy rain impact the travel intention, travel time and number of trips for non-commute related travel (Liu et al., 2015). Existing studies of the effects of weather on cycling demonstrate the impact of observed weather conditions, such as wind, total precipitation, and air temperature on cycling. As expected, generally warm and sunny weather positively contributes to walking and cycling, whereas cold, wet, and windy weather conditions show the opposite effect (Nankervis, 1999; Bergström and Magnusson, 2003; Aaheim and Hauge, 2005; Gallop et al., 2011; Sabir et al., 2011; Flynn et al., 2012; Sears et al. 2012; Thomas et al., 2013). The effect of air temperature on cycling has been found to be non-linear in the sense that weather at low air temperatures and also at high air temperatures has a negative impact on cycling (Ahmed et al., 2012; Phung and Rose, 2007; Miranda-Moreno and Nosal, 2011; Lewin, 2011; Böcker et al., 2019). Rain does not only negatively impact cycling at the specific time of cycling, but also significantly affects cycling prior to adverse weather conditions indicating behavioral anticipation (Zhao et al., 2018;

Zhao et al., 2019). Recent research on the combined effects of weather conditions on cycling in the Dutch, Danish, and Norwegian context show considerable regional differences with regard to the impact of weather on active travel (Böcker et al., 2019).

To date, research on the relationship between e-cycling and weather conditions is lacking, but it is necessary to gain insight about the commuting patterns by e-bike that are related to adverse weather conditions and to determine the potential of e-cycling as a sustainable mode of transport in transport planning. The effects of weather conditions on e-cycling likely differ from the effects on c-cycling for several reasons (Fishman and Cherry, 2016). First, use of e-bikes, generally results in shorter overall travel times due to the relatively higher speeds of e-bikes; because the duration of exposure to weather decreases, the effect of weather may be different for e-bike commuters. In most weather-cycling related studies, travel time has not been explored sufficiently, although it can be argued that the tolerance to adverse weather conditions is affected by the duration of the exposure (Böcker and Thorsson, 2014). Additionally, it can be questioned whether having access to a car and having a back-up plan to use the car under bad weather conditions will influence e-cycling as it does c-cycling.

In addition, the motor assisted peddle support feature that is associated with e-biking has a mediating effect on thermal (dis) comfort (e.g. Nikolopoulou and Steemers, 2003; Thorsson et al., 2004, 2007; Eliasson et al., 2007) and mechanical (dis)comfort (e.g. Oliveira and Andrade, 2007, see my dissertation for references), which are common effects of using a c-bike in high air temperatures (Heinen and Handy, 2012). Peddle support mediates the effect of weather on perception of thermal comfort (i.e. bodily assessment of the thermal conditions as a function of air temperature, solar radiation, relative humidity, wind speed, duration of exposure, clothing, intensity of physical activity, and bodily response in form of sweating), as it interferes with several of these elements. In addition to the possible effect of e-cycling at high air temperatures, less physical effort could negatively affect e-cycling at low air temperatures. The peddle support might further reduce the sensitivity to wind compared to the c-bike and the cycling distance might be expected to be less affected by the impact of total precipitation. Consequently, peddle support likely increases thermal comfort during hot weather (less physical activity intensity, more wind friction), and additionally reduces the discomfort of getting sweaty, reducing sensitivity to heat.

The present study is the first to systematically investigate the impact of weather conditions on expected and actual engagement in e-cycling. This investigation is based on daily commuting data over a period of 9 months, which was combined with meteorological data. The impacts of weather on e-cycling are particularly relevant for commuting because this trip type occurs throughout the year under varying weather conditions. Additionally, as a daily travel type, substituting car travel by e-bike plays an important role in making commuting more sustainable and healthier. Finally, the effects of travel behavior change intentions and car occupation are taken into account. It is likely that participants' expectations and intentions before the program will impact the extent of shifting toward e-bike use, where, according to the Extended Model of Goal-directed Behavior (EMGB) (Perugini and Conner, 2000), the addition of the desire originating from individuals' specific goals influences their behavior. Similarly, car access and having a back-up alternative might influence mode choice.

4.2 Methods

Although the Netherlands is known for cycling in daily travel, which amounts to a proportion of 28.5%, many people (48.6%) still take the car as driver or passenger to commute to work (KiM, 2018). From a sustainable mobility policy perspective, the introduction of the e-bike opens new opportunities to stimulate behavioral change of employees living a mid-range (5-15 km) distance from work (de Kruijf et al., 2018; Plazier et al., 2017). To incentivize the behavioral change from car-oriented commuting to e-cycling, the regional Noord-Brabant government developed a large-scale e-cycling incentive program (B-Riders) that targeted commuters who lived between 5 and 15 km from their work (Noord-Brabant, 2013). With approximately 1 million people (40% of all inhabitants of the region) living between 5 and 15 km from the major five cities (Eindhoven, Tilburg, 's-Hertogenbosch, Breda, and Helmond), the regional government invited people working in Noord-Brabant to participate in the e-cycling incentive program using regional newspapers and social media.

For this study, the behavior of participants in the e-cycling incentive program was monitored from January 2014 until mid-September 2014. A mixed methods approach was applied to this end using GPS data, which determined whether a commute took place and by what mode. Online surveys were conducted to assess intended e-cycling commuting behavior related to weather conditions.

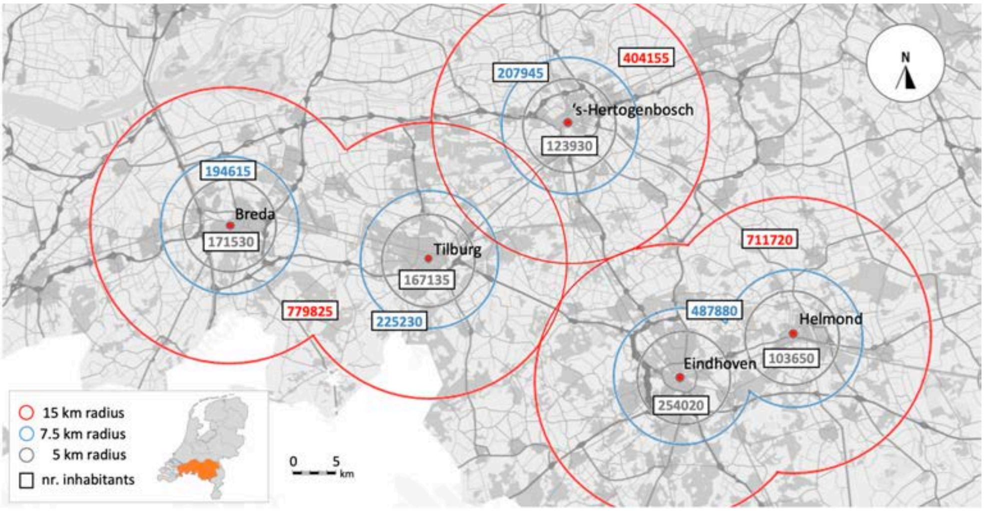

Fig. 1. Overview of the Province of Noord-Brabant, with 5, 7.5 and 15 km radius for main city centers.

The B-Riders incentive program was initiated in 2013, and specifically targeted commuters who travelled to work by car having a minimum of 50% of their working days per week. The participants had to meet three other recruitment conditions, as follows: (i) minimum commute distance of at least 3 km; (ii) 18 to 65 years old; and (iii) working in the province of Noord-Brabant, the Netherlands (Fig. 1). The region has a population of 2.5 million, with 1.9 million people living within a range of 15 km from the top five city centers.

To stimulate e-bike usage, participants were given financial compensation based on their overall e-bike participation. Because the B-Riders program was developed to reduce regional peak hour car-congestion, a differentiation between peak and off-peak was introduced with €0.15 per kilometer and €0.08 per kilometer, respectively. Participants received a maximum of €1,000 in financial incentives per person over 12 months. To make the program more appealing, participants could earn compensation for e-bike commuting and for e-cycling for other types of trips. The rough pre-study estimation made by the program was an average of 10 km of commute distance, and it would take approximately 1 year to reach the maximum financial compensation. With their explicit approval, the daily activity patterns and travel behavior of all participants were monitored 24/7 with a dedicated smartphone app provided by the program using the smartphones' GPS-sensor. In first 3 three months of the first edition of B-Riders program (which ran from September 2013 until September 2014), the tracking and monitoring technique was optimized. Because of the optimization of the data and the system as a whole, the data of the first three months is not used in this study. From January until September 2014 some participants actually reached the maximum financial incentive by e-cycling to work. The incentive program builds on previous projects in the Netherlands, in which participants received financial compensation upon changing their behavior in a more sustainable mode choice, such as the Spitsmijden (peak avoidance) project (Ben-Elia and Ettema, 2009).

4.2.2 Questionnaire

In addition to the GPS tracking, a questionnaire was administered via the internet to measure participants' intention to use e-bikes in specific weather conditions and to collect information about the sociodemographic characteristics of the study participants. According to the literature on the adaptation to e-cycling, related variables include personal and household characteristics, work-related circumstances, and spatial characteristics, which were suggested in cycling research (Fishman and Cherry, 2016; Heinen et al., 2010; Plazier et al., 2017; de Kruijf et al., 2018). To take path dependency into account in our analysis, we initially assumed that participants' habitual travel behavior before the incentive program influenced one's behavior in the program. Habit or past behavior have frequently been demonstrated to predict future behavior better than measures of intention and attitude (e.g. Bentler and Speckart, 1979; Verplanken et al., 1997; Verplanken and Aarts, 1999). We expected participants with conventional cycling commute behavior before the program to use the e-bike more frequently regardless of the weather conditions. Therefore, the same control variables are used as in recent studies.

The weather conditions were divided into air temperature (Ta), total precipitation, heavy wind (wind speed 5°Beaufort or higher), and snow/sleet. Participants were asked to report their intention to commute by e-bike to work under specific weather conditions on a seven-point Likert-scale ranging from very unlikely (1 = very unlikely) to very likely (7 = very likely). First, air temperature was dividedintothefollowinggroups:verycold(Ta <0°C),cold(0°C≤Ta <10°C),mild(10°C≤Ta <20°C),warm(20°C≤Ta <30°C), and hot (Ta ≥ 30 °C). Second, the total precipitation was categorized as follows: dry weather, light precipitation (short showers and drizzle), and heavy precipitation. Finally, participants' intention to e-bike in a heavy wind (above 5°Beaufort) and with presence of snow/sleet was documented. In addition, the questionnaire asked participants about their travel behavior during a regular week before starting to commute by e-bike and a set of questions about personal and household characteristics including gender, age, educational level, income, car ownership, household composition, and subjective health status. For each participant, the urbanization level was derived from the postal code of the home location. By adding the postal code of the work location using the GIS (Geographical Information System) fastest path analysis based on the Open Street Map cycling network, commuting e-bike distance was determined.

4.2.3 Sample demographic information

The study is based on responses from 573 participants. Table 1 specifies the composition of the total sample, including urbanization and the habitual cycling proportion before commuting by e-bike.

Table 1 shows that nearly half of the participants are between 50 and 65 years old and that most have a university or higher vocational degree. This is consistent with the publications that reported that the e-bike is especially popular in older cohorts and among higher educated segments (Fishman and Cherry, 2016; Johnson and Rose, 2013). >50% of the participants belonged to the category “couple with children living at home”. Half of the sample (48%) owned at least two cars, and most participants (55%) were in the mid to high income categories (>3,000 euro/month). Additionally, 76% of the participants had a cycle-commute distance of>10 km, suggesting that the e-bike may be an important alternative to car-commuting, which also offers acceptable travel times for longer distances. Finally, 57% of the sample had flexible working hours.

Table 1. Sample composition of 573 participants.

Variable	Category	Total
Age	25–39 years old	12.22%
	40–49 years old	39.09%
	50–65 years old	48.69%
Gender	Male	46.42%
	Female	53.57%
Education level	Lower education | primary and secondary	12.91%
	Vocational education	34.73%
	Higher education | (applied) scientific	52.36%
Car ownership	1 car	51.51%
	2+ cars	48.49%
Net household income	< 3,000	44.71%
(in € per month)	3,000 to < 4,000	35.20%
	> 4,000	20.08%
Household composition	Single	6.56%
	Single parent	3.66%
	Couple without children at home	33.93%
	Couple with children at home	55.85%
Urbanization level at home postal code	(very) strong urbanized	16.58%
	Moderate urbanized	22.51%
	Less urbanized	30.89%
	Not urbanized	30.02%
Cycle distance	0–5 km	3.66%
	5<10 km	20.24%
	10<15 km	32.11%
	15<20 km	27.40%
	20+ km	16.58%
Flexibility working hours	Yes	57.24%
	No	42.76%

4.2.4 Daily commute data

Using an integrated data imputation tool, Trace Annotator (Feng and Timmermans, 2014; Feng and Timmermans, 2019), all GPS data were segmented into journeys and stages (segments). The tool imputes, based on location of origin and destination, the specific travel purpose such as work, shopping groceries, social and recreational, for each journey based on location of facilities and information from self-reported data about facility locations. Next, the number of different modes of transport (stages) that were used during one relocation as well as the specific mode of transport per stage were determined. For this research that focused on daily commuting, GPS data was collected from January 2014 until mid-September 2014. A total of 242,179 journeys and 355,996 stages where recorded, and of these 71,772 journeys made by 573 participants from home to work were selected based on the points of origin “home” and destination “work”. Trip chains, where participants stay for limited time at a certain location (drinks after work) on their way home are accounted for as separate journey. Table 2 gives an overview of the total of journeys by all modes of transport recorded from January 2014 until mid-September 2014.

Table 2. Trips by all modes based on the purpose of 573 participants January to September 2014.

	Work	Groceries (daily)	Groceries (non-daily)	Services	Social	Recreational	Leisure	Home	Rest	Total
Total of journeys	71,772	29,184	12,872	1,23	26,623	13,29	6,081	80,31	817	242,179
Percentage purpose	30%	12%	5%	1%	11%	5%	3%	33%	0%	100%
Average journeys per person	125	51	22	2	46	23	11	140	1	423

4.2.5 Weather conditions

For this research, hourly meteorological data (air temperature, wind speed, and total precipitation) for the province of Noord-Brabant were obtained from the Dutch Meteorological Institute (KNMI, 2014) from January 2014 until mid-September 2014, which was related to the available GPS data. The province of Noord-Brabant is situated in the south of the Netherlands, consisting of 4.855 km^2 land surface, is covered by the following three meteorological stations: Gilze-Rijen (51° 34'N, 04° 56'E), Eindhoven (51° 27'N, 05° 23'E), and Volkel (51° 39'N, 05° 42'E). The region can be characterized by a warm to temperate (maritime) climate (Geiger and Pohl, 1954) with mild winters (average minimum air temperature, 7.1 °C), warm summers (average maximum air temperature, 16.3 °C), and relatively stable year-round total precipitation patterns (KNMI, 2014). To link the travel behavior to the meteorological data, participants' home postal codes were assigned to one of the weather stations. To give an indication of weather conditions in the Netherlands, Table 3 describes daily average (Tavg in *C), maximum (Tmax in *C), and minimum (Tmin in *C) air temperature, average (Ws_avg in meters per second) and maximum (Ws_max in meters per second) wind speed, and the average (Pavg in mm per hour) and maximum (Psum in mm) daily total precipitation during months of the study period in Eindhoven.

Weather effects on mobility were analyzed using meteorological variables from hourly meteorological data.

Table 3. Average daily air temperature, wind speed and total precipitation on a monthly basis from January to September 2014 (KNMI, 2014).

	T avg (°C)	T min (°C)	T max (°C)	Ws_avg (m/s)	Ws_max (m/s)	P avg (mm)	P max (mm)
January	5.8	−2.7	14.1	4.4	12.0	1.4	7.3
February	6.5	−0.6	14.0	5.3	13.0	1.5	8.1
March	8.7	−2.5	22.3	3.3	10.0	0.6	7.0
April	12.3	−1.5	23.9	3.0	10.0	0.7	6.3
May	13.6	−0.6	28.2	3.5	11.0	3.4	30.8
June	16.6	6.3	29.3	2.8	8.0	0.7	7.2
July	19.9	5.2	33.4	3.1	8.0	4.3	23.5
August	19.9	5.2	33.4	3.1	8.0	4.3	23.5
September	15.9	5.2	25.0	2.3	7.0	1.4	30.0

The reason for hourly variables is three-fold. First, the GPS data (time of departure and arrival, mode choice, distances) are collected on a continuous basis, which enables a data merge on an hourly basis. Total precipitation (Ph) is defined by the categories dry (Ph = 0 mm/hour), light total precipitation ($0 < Ph \le 2$ mm), and heavy total precipitation (Ph > 2 mm/hour). Second, commuter e-cycling is likely to be more affected by the total precipitation at the time of travel than the total precipitation on a daily level. However, it is likely that expected total precipitation in the afternoon might have an impact on the choice to go by e-bike to work in the morning. For example, when deciding to take the e-bike to work, people are likely also to consider the predicted weather for their return trip home later that day. Next to the hourly total precipitation, the afternoon total precipitation (as predicted weather) is aggregated from the hourly total precipitation from 15:00 until 19:00. Third, according to Böcker (Böcker et al., 2015), mode choice related to air temperature on the hourly level revealed roughly the same picture and performance as the average daily air temperature. Next to the hourly air temperature (Tah), for each weather station, the data are translated into the same classes as the questionnaire, enabling a comparison between the stated intention and the actual weather circumstances. Participants had to report on their intention to use an e-bike to commute to work with heavy wind (indicated by wind speed 5 Beaufort or more), which can be compared with measurements of 8 m per second by weather stations.

4.2.6 Statistical modelling techniques

To explore the impact of weather circumstances on e-cycling for all participants during their daily commute, a series of four incremental multilevel binary logistic regression analyses were performed. First, a base model explored the relationship between e-cycling and the personal and household characteristics together with urbanization level, cycling distance, and the share of past conventional cycling to work. Therefore, the proportion of regular cycling before entering the program is considered. Second, to address the impact of weather conditions, a second model added the following weather-related variables: observed air temperature when departing for work, wind speed, total precipitation when departing for time as well as the total precipitation in the afternoon period (as proxy variable for the expected total precipitation), and presence of snow/ice. In a third model, the effect of the combination between the air temperature, total precipitation, and wind speed at the departure time to work and the stated e-cycling behavior on actual e-cycling were explored. Therefore, the participants' stated intention of using an e-bike under the actually observed weather conditions was added as an explanatory variable. Finally, to test the impact of the availability of a second car in the household on the sensitivity to weather conditions, we added interaction terms between availability of a second car and gender, air temperature, windspeed, and total precipitation on e-cycling. The hypothesis was that having access to a car as a back-up plan for bad weather conditions will influence the probability of e-cycling on days with bad weather.

4.3 Results

4.3.1 Descriptive statistics

To gain insight into the relationship between the use of an e-bike or the car to commute to work based on the weather conditions, all home to work trips with their specific date and time were merged with the observed weather condition data. Table 4 shows the data for all commuting trips between January 2014 and mid-September 2014, and the relationship between the mode of transport and the momentary air temperature, total precipitation, and wind speed at the time of use. Because of the low number of observations of air temperatures below 0 °C and above 30 °C, these values are integrated into the adjacent category.

Table 4. Total number of trips per mode of 573 participants based on air temperature, total precipitation, and wind speed between January 2014 and mid- September 2014.

	Air temperature (°C)			Precipitation sum (mm)			Wind speed (m/s)	
	(very) cold T < 10	Mild 10 ≤ T < 20	Warm/hot T ≥ 20	Dry 0 mm	Light precipitation 0-2 mm	Heavy precipitation >2 mm.	Not hard (0-8 m/s)	Hard (8+ m/s)
CAR (n, %)	6,829 31%	14,036 35%	3,906 34%	10,604 31%	10,104 34%	4,063 40%	24,416 33%	355 42%
EBIKE (n, %)	15,353 69%	26,235 65%	7,592 66%	23,992 69%	19,203 66%	5,985 60%	48,684 67%	496 58%
Total	22,182	40,271	11,498	34,596	29,307	10,048	73,1	851

As shown in previous research (de Kruijf et al., 2018), the proportion of participants in the incentive program who e-cycled to work was relatively high with an average of 67%. From all three air temperature categories, the highest proportion of commuting by e-bike (69%) occurred at air temperatures below 10 °C. With an increase in the air temperature, the proportion of e-cycling in the daily commute compared to using a car slightly decreased. With total precipitation, a stronger effect was noticeable, where the use of the e-bike decreased from 69% in dry weather to 60% in heavy rain. Although there were few trips under conditions with hard winds, the proportion of e-bike use compared to the car were the lowest (58%). Combinations of these individual weather conditions influenced the choice to commute by e-bike.

Four incremental multilevel binary logistic regression analyses were performed on factors influencing the choice of commuting by e-bike or a competitive mode of transport, where each model builds upon the previous model to understand the impact of additional variables (Table 5). Overall, the four models indicate that the actual choice of commuting to work by e-bike is not systematically related to most personal and household characteristics of participants in the incentive program such as age, gender, income, or household income and composition. Only the youngest group of participants (aged 25 to 39 years old) had a significantly lower probability of e-cycling compared to the age group 50 to 64-year-olds, whereas a low household income (<3,000 euro a month) of participants (compared to high incomes) had a significantly higher probability of e-cycling as a result of the incentive program. Additionally, cycling distances above 5 km and using a c-bike to commute to work before participating in the program positively affected e-cycling.

Table 5. Binary regression analysis of weather conditions on e-cycling in daily commuting.

		MODEL 1		MODEL 2		MODEL 3		MODEL 4	
Variable	Category	B	Sig.	B	Sig.	B	Sig.	B	Sig.
Intercept		−0.1668	0.444	−0.0958	0.658	−1.7154	**0.000**	−1.6524	**0.000**
Age	25–39 years	−0.3917	**0.020**	−0.4020	**0.016**	−0.4311	**0.009**	−0.4308	**0.009**
	40–49 years	−0.0937	0.451	−0.0990	0.421	−0.1054	0.388	−0.1048	0.391
	50–64 years	-	-	-	-	-	-	-	-
Gender	Male	−0.1795	0.089	−0.1960	0.061	−0.1930	0.063	−0.2445	0.095
	Female	-	-	-	-	-	-	-	-
Physical condition	Bad	−0.1601	0.351	−0.1699	0.318	−0.1084	0.520	−0.1115	0.509
	Neutral	0.1100	0.451	0.1018	0.481	0.1314	0.359	0.1286	0.370
	Good	0.0863	0.491	0.0967	0.435	0.1231	0.316	0.1236	0.314
	Excellent	-	-	-	-	-	-	-	-
Car ownership	1 car (car1)	−0.0644	0.549	−0.0547	0.607	−0.0730	0.489	−0.1345	0.372
	2+ cars	-	-	-	-	-	-	-	-
Household income	< 3,000	0.3000	**0.019**	0.2891	**0.022**	0.2818	**0.024**	0.2844	**0.023**
(in € per month)	3,000–< 4,000	0.2401	0.065	0.2258	0.079	0.2280	0.074	0.2290	0.073
	> 4,000	-	-	-	-	-	-	-	-
Household composition	Single	−0.1339	0.593	−0.1135	0.647	−0.1096	0.656	−0.0954	0.700
	Single parent	−0.1033	0.723	−0.0787	0.785	−0.0532	0.853	−0.0406	0.888
	Couple without children	0.1949	0.440	0.1802	0.471	0.1866	0.451	0.1730	0.487
	Couple with children	-	-	-	-	-	-	-	-
Residence urbanization	(very) strong Urbanized	−0.2609	0.094	−0.2618	0.090	−0.2501	0.102	−0.2494	0.103
	moderate urban.	−0.1681	0.245	−0.1713	0.232	−0.1725	0.224	−0.1721	0.226
	Less urbanized	−0.0506	0.699	−0.0513	0.692	−0.0464	0.717	−0.0500	0.697
	Not urbanized	-	-	-	-	-	-	-	-
Cycle Distance	0–5 km	0.4792	0.107	0.5374	0.068	0.5299	0.070	0.5328	0.068
(per commute trip)	5–<10 km	0.7117	**0.000**	0.7547	**0.000**	0.7414	**0.000**	0.7408	**0.000**
	10–<15 km	0.6641	**0.000**	0.6963	**0.000**	0.6625	**0.000**	0.6610	**0.000**
	15–<20 km	0.4795	**0.003**	0.5090	**0.001**	0.4961	**0.001**	0.4951	**0.002**
	20+ km	-	-	-	-	-	-	-	-
Cycling Share	c-cycling share	0.3901	**0.019**	0.3882	**0.018**	0.3205	**0.049**	0.3248	**0.046**
Air temperature at cycling start	T < 7.5	-	-	0.6507	**0.000**	0.7179	**0.000**	0.7611	**0.000**
(in °C)	7.5 ≤ T < 12.2			0.4511	**0.000**	0.4950	**0.000**	0.5035	**0.000**
	12.2 ≤ T < 16.0			0.2339	**0.000**	0.2590	**0.000**	0.2698	**0.000**
	16.0 ≤ T < 19.1			0.2131	**0.000**	0.2269	**0.000**	0.2521	**0.000**
Wind speed at cycling start		-	-	−0.1009	**0.000**	−0.0978	**0.000**	−0.1023	**0.000**
Precipitation sum in cycling hour		-	-	−0.2508	**0.000**	−0.1352	**0.000**	−0.2379	**0.000**
Precipitation sum afternoon		-	-	−0.0147	**0.002**	−0.0108	**0.022**	−0.0107	**0.024**
Ice		-	-	−0.4854	**0.000**	−0.4921	**0.000**	−0.5017	**0.000**
Air temperature & intended behavior		-	-	-	-	0.0807	**0.000**	0.0820	**0.000**
Precipitation sum & intended behavior		-	-	-	-	0.1616	**0.000**	0.1551	**0.000**
Wind speed & intended behavior		-	-	-	-	−0.0021	0.802	−0.0022	0.796
Car possession × gender		-	-	-	-	-	-	0.1001	0.618
Car possession × air temperature	T < 7.5	-	-	-	-	-	-	−0.0172	**0.047**
(in °C)	7.5 ≤ T < 12.2							−0.0016	0.746
	12.2 ≤ T < 16.0							−0.0013	0.712
	16.0°C ≤ T < 19.1							−0.0027	0.329
Car possession × wind speed		-	-	-	-	-	-	0.0091	0.318
Car possession × precipitation sum		-	-	-	-	-	-	0.1513	**0.000**
Random effect covariance		1.290	0.000	1.342	0.000	1.313	0.000	1.288	0.000

The base model was extended with weather conditions as explanatory variables (model 2). Because of the uneven distribution of trips over the air temperature classes, air temperature is represented as quintiles (boundaries 7.5 °C, 12.2 °C, 16.0 °C, 19.1 °C). For the impact of weather conditions, the results showed that wind speed, total precipitation, and the presence of snow/ice negatively influenced te probability of e-cycling. Although it was of less impact than the total precipitation at the time of cycling, total precipitation in the afternoon (as proxy for predicted weather) had a significant impact on the choice of taking the e-bike to work. This suggests that commuters take into account expected weather conditions during the commute back home when deciding about their travel mode. An increase in air temperature also had a negative effect on e-cycling, where it might have been expected that under warmer weather circumstances, e-cycling would be more pleasant. Extending the model with the intention to cycle under specific conditions (model 3) revealed that, as expected, the stated intention of e-cycling under the observed weather conditions had a positive effect on e-cycling probability for air temperature and total precipitation, but not for wind speed.

Finally, we extended model 3 with interaction to account for moderation effects of weather conditions by car access (model 4). This model indicates that participants from multiple person households with only one car had fewer alternatives under poor weather conditions and they were more likely to e-cycle. For specific weather conditions, we found that both the combinations between car possession and heavy wind as well as car possession and air temperature had no significant impact on e-cycling, except at relatively low air temperatures (below 7.5 °C). However, participants with two or more cars in their household were less likely to e-cycle. Although gender was shown to be an influential factor for conventional cycling in previous studies, there was no significant relationship between gender and car possession compared to e-cycling.

4.4 Discussion

This paper reported on the impact of objective weather conditions on e-cycling within an e-cycling incentive program in the province of Noord-Brabant, the Netherlands. In the program, participating car-commuters were incentivized to use of e-bikes in daily commuting, earning monetary incentives for each kilometer that they e-cycled. With a longitudinal design based on GPS-data and objective meteorological data, this study observed the impact of weather conditions on e-cycling. The main objective was to gain insight into e-cycling behavior under adverse weather conditions, where the use of the e-bike would mitigate range restrictions and physical effort, which are main barriers in conventional bicycle use for daily commuting (Heinen et al., 2010; Heinen and Handy, 2012). This is because of the electric peddle support of the e-bike.

Our study showed that e-cycling was affected by weather conditions, especially air temperature, total precipitation, wind speed, and the presence of snow/ice. Although snow and ice were not common weather occurrences during the study period, the presence of snow and ice on the cycle path had the highest impact on the choice not to commute to work by e-bike. Second, where a positive effect might have been expected on the relationship between e-cycling and air temperature, actual e-cycling behavior showed the opposite effect. This remain remarkable, as outcomes of previous studies showed that high air temperature has a negative impact on cycling only for heat with air temperatures above 25°Celcius (Ahmed et al., 2012; Phung and Rose, 2007; Miranda-Moreno and Nosal, 2011; Lewin, 2011; Böcker et al., 2019), where it should be noted that in our study, high air temperatures were less frequent compared with other studies, with a maximum air temperature of 33.4 °C. Third, both heavy winds and total precipitation negatively influenced e-cycling, where total precipitation had the higher impact than heavy winds. The lower impact of heavy wind on e-cycling may be because the electric peddle support partly mitigates the (negative) physical effort of the conventional bicycle (Heinen et al., 2010). In practice, combined effects of weather conditions occurred and influenced e-cycling.

Although recent studies report about the adaptation of the e-bike mostly for the older age groups, male gender, and a higher educational level (Fishman and Cherry, 2016; Kroesen, 2017), in this study, only the youngest age group (below 40 years old) e-cycled significantly less compared to the oldest group of working people. This indicates that e-cycling has become more common in recent years in the middle-aged commuter group, which might be related to the life phase where households with young children for example need more trip chains in daily activity patterns. To date, many studies have focused on either behavioral intention or on a behavioral change (G¨arling and Fujii, 2009). Our study shows that participants who stated before the study that they had a high intention of using the e-bike under adverse weather conditions showed significant positive actual behavior during the program for air temperature and total precipitation, as might have been expected.
However, there is no direct and significant relationship between a heavy wind in combination with the intended and the actual e-cycling behavior. It can be argued that the peddle support only partly mitigates the extra physical effort that is required because of strong winds than expected by participants before the program, causing differences between the intended and actual behavior under strong winds.

These weather circumstances could, therefore, be less of an impact on e-cycling in daily commuting than on conventional cycling, strengthening the reasoning from a policy perspective to invest in e-cycling as environmentally friendly alternative to car commuting. As not all population segments are equally interested in arguments of environmentally friendly behavior change, a more specific target group approach is therefor recommended. Finally, this paper established to what extent availability of a car as an alternative to the e-bike in combination with gender and specific weather conditions affects e-cycling. Although previous research has shown differences in the e-cycling behavior between men and women (de Kruijf et al., 2018), the combination of gender and car availability did not affect e-cycling significantly in this particular study. The total precipitation in combination with car possession, however, was shown to have a significant impact on e-cycling. Participants with only one available car in the household tended to e-cycle more under rainy circumstances than those with an available car as an alternative. Additionally, air temperature in combination with car possession by the household slightly affected e-cycling. Although the e-bike mitigates the effects of effort compared to the conventional bicycle and increases commuting via cycling for mid-range distances (de Kruijf et al., 2018), adverse weather conditions somewhat limit the choice to leave the car permanently. However, from a policy perspective, the study shows that both men and women more often choose to commute to work by e-bike than by car, indicating that the e-bike can be regarded as a structural commuting mode of transport for short and mid-range distances despite light adverse weather conditions. This could be because of a conscious choice related to the higher purchase value of the e-bike compared to the conventional bicycle. Where the effects seem positive, the extent of these effects can be argued in relation to the e-cycling incentive program conditions. The results of the present study can be helpful for further strengthening Dutch cycling policies which target commuter cyclists. For example, commuters being less sensitive to changes in weather conditions in combination with the development of high quality and safe regional cycling routes decreases existing mental, natural and physical barriers (Heinen et al., 2010) and increases the bicycle use in daily commuting. Given the rapidly increasing sales rate (38%) of e-bikes between May 2019 and 2020 (BOVAG, 2020), and the government and employer led incentive programs, e-bikes could function under many weather circumstances as a sound alternative for car-commuting. Although it is likely that not all commuters will fully switch to using e-bikes in all weather conditions, a vast amount of car-commuting trips can be substituted with effective cycling policy measures (de Kruijf et al., 2018).

Overall, the results indicate that e-bikes have a clear potential to substitute car use in commute trips. A reduction in car use of more than 60% is very significant and raises the question whether the car is still needed as a back-up in case of e.g., adverse weather conditions, or whether this could be fulfilled by public transport or forms of shared mobility. Answering this question is speculative and requires insight into the reasons of using the car. If this reason is adverse weather, (almost) door-to-door services such as car sharing may be more attractive than public transport, which still requires access and egress travel often by walking or cycling. The variation in car share across weather conditions suggests, however, that weather is not the main reason for car use. Another possible reason for car use may be the opportunity to have more complex trip patterns, have serve passenger trips etc. Such needs or not likely met by public transport, but more likely by shared mobility options, suggesting some potential for these services to replace private car trips. Further research will be needed to explore this.

This study had some limitations. First, the research was based on a large-scale e-cycling incentive program, where car-commuters were incentivized to switch to e-cycling on a voluntarily basis. It remains unclear if commuters would show comparable behavior without participating in an incentive program because their personal and household characteristics as well as the social context may vary, and their motivation to take up e-cycle may also vary. It, therefore, remains uncertain to what extent participants' behavior deviates from average where participants in the program are more likely to commute via e-cycling. Second, it remains uncertain to what extent the weather conditions affected e-cycling for other travel purposes and in other spatial contexts. Because of the regional nature of the incentive program, similar effects are not expected in other contexts (e.g., in different geographical contexts or without providing incentives). For the relationship between active travel and weather circumstances in different countries, these variations are already confirmed (Böcker et al., 2019). Third, it is uncertain if similar behavior is shown by the participants over a longer period compared to the current study. Behavioral changes brought about by incentive programs (Ettema et al., 2010) will not necessarily be sustained when the incentive ends.

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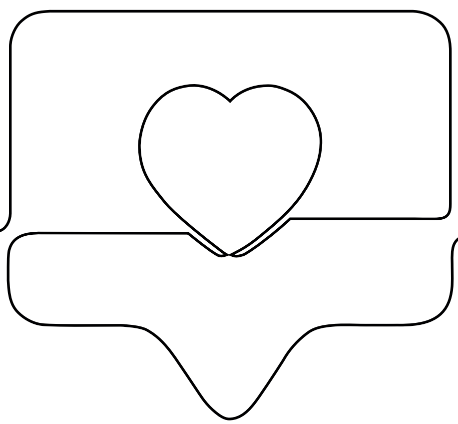
CHAPTER 5

A longitudinal evaluation of satisfaction with e-cycling in daily commuting in the Netherlands



Abstract

This paper reports on the effects of an e-cycling stimulation program on travel satisfaction in the province of Noord-Brabant, the Netherlands. The program was designed to stimulate car-commuters to shift to e-bike in daily commuting, earning a monetary incentive for each kilometre e-cycled. With a longitudinal design, this study shows a significant increase in travel satisfaction when switching from car to e-bike. Starting from an average slightly positive satisfaction with car commuting, participants reported an extremely positive expected travel satisfaction by e-bike. Although a bit less than expected, the experienced travel satisfaction with e-cycling was high after a period of a month and even increased in the following period of half a year. Where the participants can be sub-divided into car-only and multimodal car-commuters, this distinction does not show in the experienced travel satisfaction with e-cycling. Our study indicates that the hedonic treadmill mechanism does not automatically apply to the satisfaction with e-cycling. Multivariate analyses suggest that the increase in the travel satisfaction is affected by self-reported health, car ownership, urbanization degree, whether car use and e-cycling are experienced as strenuous, congestion on the route and the attractiveness of the cycle route.

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5.1 Introduction

Cycling is widely regarded as a travel mode that is not only environmentally sustainable, but also contributing to a better health as a result of the physical activity involved (e.g. Morris and Hardman, 1997). An additional advantage of cycling is that is associated with better mood during travel (also termed travel satisfaction) as compared to motorized travel modes such as car and public transport. This effect is observed across cultures and geographical contexts (see Olsson et al., 2013; Mao et al., 2016; St-Louis et al, 2014; De Vos et al., 2015), suggesting that it is the intrinsic characteristics of cycling, such as the level of physical activity and exposure to outdoor environments, that are responsible for the higher levels of travel satisfaction (e.g. Ekkekakis et al., 2008). Various studies indicate that the positive effects on mood and well-being are not limited to the duration of cycling, but extend to other periods of the day and are even associated with higher satisfaction with life (e.g. Martin et al., 2014; Friman et al., 2017a). Despite its positive effects, cycling is not an option for many trips, due to (amongst others) its limited distance range (as a result of lower speed) and physical limitations that apply to part of the population (Popovich et al., 2014, MacArthur et al., 2014).

E-cycling has been introduced over the past decade in the Netherlands as a way to overcome limitations of distance and physical limitations, by providing additional peddling support. E-bikes used in the Netherlands require the cyclist to peddle, but lead to higher speeds with the same effort, or the same speed with less effort. This is in contrast to for instance Chinese e-bikes, that do not require peddling and therefore can be considered electric mopeds. The scope of this paper is on e-cycling with peddle support. Over the past decade, e-bikes with peddling support have obtained a non-trivial market share in various places in the world (e.g. Fishman and Cherry, 2016). This raises questions about the health and well-being effects of a shift from other travel modes to e-cycling. A key observation in this respect is that among the rapidly increasing pool of studies that have investigated satisfaction with travel for a variety of modes and in various contexts, travel satisfaction using e-bikes with peddling support has not yet been addressed. Hence, insight into this aspect is highly needed. A second important notion is that those taking up e-cycling use their e-bike for an important part to make trips they previously made by other modes. Hence, their shift in travel mode may be accompanied by a change in travel satisfaction (Abou-Zeid et al., 2012). Studying such a shift is important in order to learn about the well-being effects of a shift to e-bike beyond the mere health effects, but also since mood or satisfaction associated with new behaviors may be an important predictor of adherence to the new behavior (Standage and Ryan, 2012). An additional relevant issue in this respect is how travel satisfaction will develop over a longer period, as this may have implications for adherence on the longer term.

To address the effects of a shift to e-cycling on travel satisfaction, this study uses unique longitudinal data of satisfaction with the commute trip among participants in a programme (B-riders) that stimulated car commuters to shift to e-bike use for their commute trip. Using travel satisfaction data of their commute trip by car before the programme and by e-bike on several points in the programme, conclusions are drawn regarding the direct and longer-term effects of the shift to e-bike on travel satisfaction, and on the personal and contextual factors influencing these effects. The paper is structured as follows. Section 2 outlines the literature. Section 3 describes the research and data collection methods. Section 4 analyses the changes in travel satisfaction and the potential underlying reasons for this change. Section 5 concludes on the results of the research.

5.2 Literature review

5.2.1 Travel satisfaction: concept

Travel satisfaction can be regarded as satisfaction with a specific life domain (next to domains such as family life, professional life, etc.) and as such is as a concept related to subjective well-being (SWB). SWB is an overall assessment made by individuals of their life, and is usually assumed to consist of three components: a cognitive assessment of one's life conditions, positive affect and negative affect (Diener and Suh, 1997). Cognitive life satisfaction is often measured using the Satisfaction with Life Scale (SWLS) (Diener et al., 1985; Pavot and Diener, 1993), which consists of five self-report items (e.g. "Overall I am satisfied with my life") which are rated on a scale ranging from "totally disagree" to "totally agree". Alternatively, Cantril's Self Anchoring Scale has been used, in which respondents rate their life on a ladder ranging from 0 ("worst possible life") to 10 ("best possible life"). The affective component refers to the frequency and intensity of positive and negative emotions, and is measured using scales such as PANAS (Positive and Negative Affect Scale) or the Swedish Core Affect Scale (SCAS) (Västfjäll and Gärling, 2007). In PANAS, respondents indicate for a number of distinct emotions to what extent they experience each emotion. SCAS is a dimensional scale, in which emotions are measured along two dimensions: valence and activation.

Measurement of cognitive life satisfaction refers to a longer term steady state, assuming that life satisfaction is reasonably constant, as long as one's basic life circumstances do not change. Measurement of affect typically refers to a momentary state, asking for emotions felt at a particular time. However, cognitive and affective components are also measured on shorter and longer time scales. For instance, it is common to ask for frequency of emotions, or average affective state over periods lasting for instance a day or a week (Friman et al., 2017b).

Travel satisfaction can be regarded as a subdomain of life satisfaction. In various studies, positive correlations between travel satisfaction and life satisfaction have been found, in the same way as satisfaction with other life domains contributes to life satisfaction. In this paper we assume that, similarly to subjective well-being, travel satisfaction includes both cognitive and affective components. Ettema et al. (2011) developed the Satisfaction with Travel Scale (STS), which includes 3 cognitive and 6 affective items. This scale has been tested in a variety of contexts, and it was consistently found that both the cognitive and affective dimensions were in logical ways related to travel circumstances. This implies that travellers develop an evaluation of their travel experience, which indicates how good or pleasant travel is, and how this experience can be improved through service and design factors. Apart from the STS-scale, travel satisfaction has also been measured with multiple items in a cognitive scale (Bergstad et al., 2011) and via single item measurements (see Mao et al., 2016). General findings about the factors influencing travel satisfaction are fairly consistent between these studies. In addition, travel satisfaction can be measured on different time scales. The concept and measurement scales have been applied to measure satisfaction with a concrete single trip (e.g. Mao et al., 2016), with a repeatedly made trip of a particular type (such as commuting, see St-Louis et al., 2014) or with one's general travel conditions (Friman et al., 2017b).

Travel satisfaction is reported by travellers directly, rather than derived from displayed behavior, as is common practice in utility based discrete choice modelling (Ettema et al., 2010). On a conceptual level, this comes down to a distinction between decision utility (the expected outcome when a decision is made) and experienced utility. Various empirical studies indicated that experienced utility and decision utility are not the same. The underlying reason is that people are not necessarily very good at predicting their emotional responses to upcoming events. In addition, choices may be made under constraints, such as financial constraints, preventing individuals from choosing their preferred alternative. Given the difference between decision utility and experienced utility, experienced utility is a useful indicator of the effect that travel under particular circumstances has on a traveller's experience, which may have implications for his/her overall well-being (Friman et al., 2017b; De Vos et al., 2017). Relying on decision utility, as derived from observed choices, could potentially lead to biased results when determining the outcome of interventions in cost-benefit analysis.

5.2.2 Travel satisfaction: empirical findings

Studies of travel satisfaction have been carried out across a variety of geographic and cultural contexts, but certain outcomes have been found consistently. First, a major factor affecting travel satisfaction is travel mode. Consistently, active travel modes (walking, cycling) are evaluated as giving a higher satisfaction than car and especially public transport (see Olsson et al., 2013; Mao et al., 2016; St-Louis et al, 2014; De Vos et al., 2015). This higher satisfaction with active modes has been ascribed to the physical activity involved and resulting in the optimal level of arousal. Furthermore, factors influencing travel satisfaction differ between travel modes. For car travel, factors such as independence, freedom, prestige and mastery add to a positive travel satisfaction (Jakobsson Bergstad et al., 2011, 2012; Steg, 2005). However, factors such as congestion, leading to stress, and long travel times may make car use less attractive, leading to lower travel satisfaction. Other factors that may negatively affect travel satisfaction with the car include experienced unsafety, crowdedness and distraction by billboards (Ettema et al., 2011).

Public transport (PT) is usually evaluated as less attractive compared to active travel and car use. Factors affecting satisfaction with public transport include seat probability, frequency of service, cleanliness and safety (Redman et al., 2013; Stradling et al., 2007). In addition, the type of public transport influences travel satisfaction. Various studies found that rail transport is evaluated more positively than bus transport (St-Louis et al., 2014). Ettema et al. (2016) report that also quality, readability and design of stations and public transport stops may have a significant impact on travel satisfaction. With respect to active travel, few studies directly compare travel satisfaction with walking and cycling. Also, while many studies have investigated the factors influencing walking and cycling levels, research into the factors influencing satisfaction with walking and cycling has been limited. Factors that were found to affect travel satisfaction for active modes include climate and weather (temperature, precipitation) as well as darkness and shimmer (Böcker et al., 2015). Also, the cycling environment plays a role. More lively and aesthetic environments (Mambretti, 2011; Eliasson et al., 2007) are found to influence travel satisfaction positively, while experienced unsafety leads to a lower travel satisfaction (Ettema and Smajic, 2015). Next to the aesthetics, social aspects of place valuation (Cattel et al., 2008) influence the experience of cycling, such as the outdoor presence of people (Lin, 2009, Thorsson et al., 2007; Zacharias et al., 2001). Perceived safety, friendliness, liveliness and social interactions in outdoor public space might also positively affect emotions during cycling (Kööts et al., 2011). Notably, however, no studies to date have addressed travel satisfaction with e-bike, nor the personal or contextual factors influencing it.

5.2.3 Travel satisfaction and mode change

Given the differences in travel satisfaction between modes, the question arises how travel satisfaction changes in case of a shift in travel mode. This issue is of particular importance given policies and interventions aiming to bring about a mode shift, such as the e-bike stimulation program in this study. Cross sectional surveys as reviewed above are not necessarily a good base for estimating mode shift effects, as they ignore selection effects, leading travellers to choose the travel mode of their preference.

From a theoretical point of view, a change of travel mode will be at least partly driven by an expectation of the travel satisfaction derived from the new travel mode. Previous research revealed that individuals are reasonable capable of predicting the valence of their future experience, but much less capable of predicting the intensity and duration of their experience. This is due to various mechanisms. The forecasting bias (Wilson and Gilbert, 2003) holds that predictions of future experiences are based on the memory of previous experiences, and extreme experiences are more likely to be remembered. As a result, people will overestimate the intensity of positive and negative emotions of future events. The focusing illusion (Schkade and Kahneman, 1998) states that when anticipating an event, people tend to focus on a particularly good or bad aspect of it, and therefore expect the event to be either very good or very bad. In reality, this aspect is only one of many aspects influencing the experience, so that the experience will likely be more moderate.

With respect to the longer term stability of the experience, the hedonic treadmill mechanism is relevant (Diener et al., 2006). This implies that when circumstances improve (e.g. using a more attractive travel mode), this will initially result in improved well-being. However, gradually, the changed circumstance will be regarded as the standard, implying that aspiration levels will be raised, and well-being returns to its initial base level. This effect is strengthened as individuals will over time pay less attention to the improved factors in their circumstances. This diminishes the intensity of the emotional impact and the effect on well-being and mood.

Limited empirical work in longitudinal analysis of travel satisfaction confirms that travellers misestimate their travel satisfaction with a new travel mode. Studies in the US (Abou-Zeid and Ben-Akiva, 2012), Switzerland (Abou-Zeid et al., 2012) and Norway (Pedersen et al., 2011) all found that car users, when shifting to public transport as part of an intervention, experienced a higher travel satisfaction than they had expected. In the US and in Swiss studies, heterogeneity was observed in the responses with one group appreciating public transport much more than the other group, which had clear impact on their public transport use following the intervention.

5.2.4 Research gaps and hypotheses

The above overview suggests that empirical insight in travel satisfaction associated with e-cycling is lacking. This study will fill this gap, and will compare travel satisfaction with e-cycling with travel satisfaction by car for of a sample of car commuters. E-cycling bears similarities to conventional cycling in the sense that one is directly exposed to the environment and will experience weather, noise, pollution and other traffic directly. As conventional cycling, e-cycling requires physical effort, although this is significantly less than for conventional cycling with a similar speed. On the other hand, commuters may use the e-bike to travel faster with a similar input of physical activity, in order to cover larger distances. Based on these considerations and the widely reported high satisfaction with cycling, we expect that travel satisfaction with e-cycling will be higher than travel satisfaction with car use, and that a shift from car to e-cycling thus is associated with an increase in travel satisfaction. Regarding travellers' expectations, both the focusing illusion and the forecasting bias suggest that positive aspects of e-cycling will be overestimated, and thus that actual travel satisfaction with e-cycling will be lower than expected. With respect to travel satisfaction on the longer term, the hedonic treadmill effect suggests that following an expected increase in travel satisfaction as a result of the mode shift, travel satisfaction will decrease once travellers get used to the positive experience of e-cycling.

5.3 Materials and methods

5.3.1 Study design

With the e-cycling incentive program (B-Riders), the province of Noord-Brabant in the Netherlands aimed to stimulate a switch from car towards the use of the e-bike. From 2013 to date (2018) the program has been targeting car-commuters to participate. E-bike use was stimulated by giving participants financial compensation depending on their e-bike use. With the reduction of car-congestion as the main reason for the B-Riders program, the financial incentive in the peak hours was set at €0.15 per kilometre. In the off-peak period participants received €0.08 per kilometre with a maximum of €1000 per person overall. Incentives could be earned not only when using the e-bike for commuting, but also for other purposes. With an average of 10 km of cycling-commute distance, it would take up to a year to reach the maximum financial incentive. The program builds on previous projects in the Netherlands, in which travellers received incentives upon changing their behavior in a desired direction, such as the Spitsmijden (peak avoidance) project (Ben-Elia and Ettema, 2009). E-bike use was monitored using a smartphone app that tracked participants' travel behavior using GPS. From these GPS-tracks e-bike use was derived. Participants had to meet four recruitment conditions: (i) conducting at least 50% of their commuting trips a week by car before entering the program, (ii) the commute distance should be at least 3 km, and (iii) being between the age of 18 and 65 years old and (iv) working in the province of Noord-Brabant.

In order to measure behavioral change and satisfaction with travel, three questionnaires were conducted. The baseline questionnaire recorded the travel modes used in a regular week before starting to commute by e-bike. In addition, respondents reported their experienced satisfaction with current car-travel to work, their expected satisfaction with e-cycling to work and a set of personal and household characteristics. Personal and household characteristics included gender, age, educational level, income, car ownership, household composition and subjective health status. In addition, perceived characteristics of the commute by car and e-cycling were asked. The second questionnaire was held a month after the start of participation in the program. It included questions about frequency of travel modes used for commuting (including the e-bike), and experienced satisfaction with the e-bike commute. In addition, it included questions about the experienced characteristics of the e-bike commute and the landscape. The third questionnaire, held six months after entering the program, again recorded the frequency of travel modes used for commuting (including the e-bike) and experienced satisfaction with the e-bike commute and change in physical health since entering the program. In addition, it included questions about the experienced characteristics of the e-bike commute and the landscape. Cycling distance and level of urbanization of each participant were derived based on zip-codes of the home and work locations in combination with the existing cycling network in Open Street Map.

5.3.2 Measuring satisfaction with travel

Key to the study is to investigate the relationship between behavioral change from car to e-cycling and the satisfaction with the commute trip. Participants' satisfaction with their commute trips was measured using the Satisfaction with Travel Scale (STS) (Ettema et al., 2011). The STS is based on methods developed to measure subjective well-being (SWB), which is defined in terms of an individual's cognitive and emotional well-being (Diener et al., 1985). Cognitive well-being refers to an individual's cognitive assessment of his or her life in general. Affective well-being refers to an individual's emotional state. As satisfaction with travel can be regarded as a form of domain specific SWB, it is measured in a way of analogous to SWB. The affective component of satisfaction with travel is based on the affect circumplex (Västfjäll and Gärling, 2007). In this conceptualization, each emotion can be defined according to two dimensions: valence (how good or pleasant is the experience) and activation. In the STS, endpoints of items used to measure affective well-being are defined as combinations of the valence/activation dimensions. Three items range between positive deactivation [−3] (e.g. relaxed) and negative activation [3] (e.g. time pressed). Another three range between positive activation [3] (e.g. alert) and negative deactivation [−3] (e.g. tired). Finally, three sub-scale items were designed to measure cognitive well-being derived from the commute trip. In the questionnaire the order between the subscales was counterbalanced. The items and endpoints included in the STS are summarized in Table 1. STS has been applied to measure travel satisfaction with car, various public transport options, walking and cycling (e.g. Olsson et al., 2013; De Vos et al., 2015) and recently also with e-bikes in China (Ye and Titheridge, 2017), which differ from the e-bikes in our study in that no peddling is required. As the STS has resulted in consistent results across travel modes in a variety of geographic settings, we believe it is a suitable approach to measure satisfaction with e-cycling in this study.

Satisfaction with travel scores were constructed for each respondent by averaging the ratings for each of three subscales. Next, one satisfaction with travel score for each respondent was constructed by averaging the ratings of all nine items.

5.3.3 Analyses

To explore the changes in satisfaction with travel along the study, we first carried out descriptive analyses of the STS averages sub-divided by all three STS sub-scales and a general satisfaction with travel score. The general satisfaction with travel was calculated by averaging across the three subscales. A test of the structure of the scale suggests that all three subscales contribute to a similar extent to an overarching construct of travel satisfaction (Friman et al., 2013). This was done for all participants before starting (Baseline), one month after starting to participate in the program and half a year after starting to participate.

Table 1. End points of the satisfaction with travel scale.

Positive deactivation-negative activation (items 1-3)	
… I feel stressed	… I feel calm
… I feel hurried	… I feel relaxed
… I feel worried arriving too late	… I feel confident arriving on time
Positive activation-negative deactivation (items 4-6)	
… I'm bored	… I'm enthusiastic
… I'm tired	… I'm alert
… I'm fed up	… I'm engaged
Cognitive evaluation (items 7-9)	
… Travel was laborious	… Travel was prosperous
… Travel was uncomfortable	… Travel was comfortable
… I experience my trip as bad	… I experience my trip as optimal

Table 2. Sample composition of participants.

Variable	Category	Total	Car	Multi-mode
Age	25-39 years old	12%	15%	11%
	40-49 years old	37%	34%	38%
	50-65 years old	51%	51%	51%
Gender	Male	48%	45%	50%
	Female	52%	55%	50%
Education	Low	17%	17%	17%
	Medium	27%	26%	28%
	High	56%	58%	55%
Subjective health status	Bad	14%	17%	12%
	Neutral	18%	17%	19%
	Good	33%	33%	33%
	Excellent	35%	33%	36%
Car ownership	1 car	50%	45%	52%
	2+ cars	50%	55%	48%
Household income (in € per month)	< 3.000	35%	28%	38%
	3.000 - < 4.000	28%	23%	30%
	> 4.000	16%	18%	15%
Household composition	Single	7%	6%	7%
	Single parent	2%	2%	2%
	Couple without children	35%	40%	33%
	Couple with children	56%	52%	58%
Urbanization	(very) strong urbanized	15%	11%	17%
	Moderate urbanized	23%	26%	21%
	Less urbanized	32%	33%	31%
	Not urbanized	30%	30%	30%
Cycle distance	0-5 km	4%	1%	5%
	5<10 km	19%	13%	22%
	10<15 km	31%	30%	31%
	15<20 km	29%	30%	28%
	20+ km	18%	26%	14%
Flexibility working hours	Yes	60%	62%	59%
	No	40%	38%	41%
Number of commute days per week	1-3 days a week	14%	26%	9%
	4 days a week	33%	31%	33%
	5 days a week	53%	43%	58%
Frequency of cycling commute at baseline	0 days a week	37%	100%	7%
	1 day a week	20%	-	30%
	2 days a week	19%	-	28%
	3+ days a week	24%	-	35%
Frequency of car commute at baseline	1 day a week	25%	1%	18%
	2 days a week	18%	11%	12%
	3 days a week	25%	16%	13%
	4 days a week	18%	21%	6%
	5 days a week	14%	50%	50%
Reported change in health status	Δ Very bad – very good	0.12	0.26	0.05
Perceptions of commute trip when e-cycling				
Strenuous car commute	Not at all (1) – very much (7)	3.15	2.99	3.22
Strenuous E-cycling commute	Not at all (1) – very much (7)	2.89	3.18	2.75
Crowdedness during commute	Very quiet (1)– very busy (7)	3.27	3.19	3.31
Freedom of speed determination	Completely under control (1)– strongly determined by fellow road users (7)	2.59	2.58	2.60
Annoyed by road users	Not at all (1) – very much (7)	2.96	2.83	3.02
Threatened/Unsafe by road users	Not at all (1)– very much (7)	2.40	2.26	2.46
Route unsafety	Not at all (1)– very much (7)	2.83	2.77	2.86
Wayfinding	Very easy (1)– very difficult (7)	1.32	1.34	1.30
Distraction by billboards	Not at all (1) – very much (7)	1.85	1.84	1.86
Perceived characteristics of commute landscape when e-cycling				
Green	Very little green (1) – very green (7)	5.42	5.54	5.36
Openness	Sheltered (1) – open (7)	4.71	4.72	4.71
Aesthetics	Beautiful (1) – ugly (7)	2.93	2.81	2.98
Liveliness	Lively (1) – boring (7)	3.14	3.18	3.12
Atmosphere	Comfortable (1) – distant atmosphere	2.91	2.94	2.90
Height difference	A lot of (1) – little (7)	5.49	5.62	5.43
Landscape	Varied (1) – monotonous (7)	3.25	3.18	3.29
Urbanization	Not (1) – very strong (7)	2.97	2.81	3.05

To investigate possible differences between car-only and multimodal car-commuters, analyses are carried out for each group separately. Next, we carried out regression analyses of the change in the nine-item overall satisfaction with travel when shifting from car use to e-cycling for the expected change as well as the change after one and six months. Based on the factors reported to influence travel satisfaction, explanatory variables include personal, household and commute characteristics, as well as route and spatial context characteristics as explanatory variables. Following Ettema et al. (2013), we include aspects resulting from the interaction with other road users in the analyses (see Table 2). Similarly, we include aspects related to landscape characteristics, based on literature review (see Table 2). This allows us to draw conclusions about the factors that influence the satisfaction with e-cycling within the e-bike stimulation program relative to the satisfaction with the car commute at baseline, and how the importance of these factors might change over time.

5.3.4 Sample descriptives

The study is based on responses from 547 participants. One group of participants only commuted by car during the baseline measurement (n = 172), another group combined commuting by car with other modes (n = 375) in the baseline measurement. Sample characteristics are shown in Table 2, including characteristics of the commute and perceived landscape characteristics.

Table 2 shows that more than half of the participants is between 50 and 65 years old and highly educated. This is in line with the literature reporting that e-bike is especially popular among older age cohorts (Fishman and Cherry, 2016). 70% reported a good or excellent health. More than 50% of the participants belongs to the category 'couple with children'. Half of the sample owns at least two cars, and the majority of participants (54%) falls in the higher income categories (> 3.000 EURO/month). 78% of the participants has a cycle-commute distance longer than 10 km, suggesting that the e-bike may be an important alternative to car-commuting, which offers acceptable travel times also for longer distances. Finally, about 60% of the sample has flexible working hours.

Car-only commuters and multimodal car-commuters do not differ substantially on most characteristics. However, the percentage of longer distance commuters (20+ kilometres) for car-only commuters is higher, and this group more often has two or more cars in the household and more often has a higher income.

5.4 Results

5.4.1 Descriptive analyses

Table 3 shows the average STS scores at baseline, after one and after six months per STS sub-scale and the overall STS score per participant. Significance (p-values of an independent samples T-test) of the differences is shown in Table 4. Although the experienced satisfaction with car commuting at baseline is positive, indicating a positive experience of the car commute, both the expected satisfaction with e-cycling (baseline) as well as the experienced satisfaction with e-cycling (after one and six months) are significantly higher for all participants. This holds for the aggregate nine-item STS score as well as the three subscales. Hence, both affective experience and cognitive assessment of e-cycling is better than of the original car commute. In addition, it is important to note that the large increase in travel satisfaction is found both for commuters only using the car at baseline and those occasionally cycling. Apparently, the e-bike is an attractive alternative for the car commute, irrespective of cycling experience in commuting. The size of the increase (1.4 units for the overall STS for all participants) is markedly larger than the differences between satisfaction with cycling and car use in previous cross-sectional studies using the STS (e.g. 0.3 in Sweden (Olsson et al., 2013). This may be due to the difference between e-cycling and conventional cycling, but also to the effect of a behavior change having a positive effect in itself.

Comparison between the experienced STS after one and six months and the expected satisfaction with e-cycling at baseline shows that experienced STS of e-cycling after one month is somewhat lower than at baseline. This difference occurs in the aggregated STS and the subscales, and turns out to be statistically significant for only-car as well as multimodal commuters. Hence, participants seem to overestimate their travel satisfaction. Nevertheless, the increase in experienced STS as compared to commuting by car is much larger than the small difference with the expectation. Experienced STS after six months shows an increase in multimodal commuters compared to after one month, bringing the experienced STS back to the initial expectations on most STS subscales, although experienced positive activation levels remain somewhat lower than the initially expected level. Apparently, over a 5-month period, multimodal commuters learn to appreciate e-cycling more. This trend shows up to a somewhat lesser extent for car commuters, but does not turn out to be statistically significant.

Of the STS subscales, the subscale ranging between negative activation and positive deactivation has the highest average. This suggests that across modes and times, the commute is relatively calm and relaxed. An interesting finding is that the positive activation score is lower than the cognitive evaluation for the car commute, but higher for the e-bike commute. Likely, the physical activity involved in e-cycling makes commuters more alert, engaged and enthusiastic. Logically, the group of car-only car-commuters show higher satisfaction with car-commuting.

5.4.2 Regression models of change in travel satisfaction

In order to investigate how travel satisfaction changes with a shift from car commuting to commuting by e-bike, regression analyses were carried out on the difference in travel satisfaction between:

1. The expected travel satisfaction by e-bike at baseline and the travel satisfaction by car at baseline;
2. The travel satisfaction by e-bike after one month and the travel satisfaction by car at baseline;
3. The travel satisfaction by e-bike after six months at baseline and the travel satisfaction by car at baseline;

Explanatory variables included household characteristics (gender, age, health status, household income, education, household composition, urbanization level and car ownership) and work place related circumstances (flexibility of start and end time, travel days to work, cycling distance). In addition, we included commute related characteristics such as the level of effort, crowdedness on the route, freedom of speed determination, annoyance by other road users, perceived route unsafety, wayfinding and distraction by billboards, as well as the share of habitual commute cycling at baseline. Because we might expect a difference between car-only commuters and multimodal car-commuters a dummy variable was included denoting whether someone is a car-only commuter. Finally, to investigate the impact of the spatial context on satisfaction with travel during e-cycling, the perceived degree of green, openness and liveliness together with the aesthetical value, atmosphere, height differences and perceived urbanization were added.

Table 3. Satisfaction with car-commuting (baseline), expected e-cycling (baseline) and experienced e-cycling after one and six months.

Variable	Car experience baseline	Expected E-bike baseline	E-bike experi-ence after one month	E-bike experi-ence after six months
All participants (N=547)				
Positive deactivation - negative activation	0.87	2.18	2.05	2.15
Positive activation - negative deactivation	0.27	2.06	1.85	1.92
Cognitive evaluation	0.55	1.83	1.66	1.78
Satisfaction with travel	0.56	2.02	1.85	1.95
Only car-commuters (N=172)				
Positive deactivation - negative activation	1.05	2.15	2.02	2.09
Positive activation - negative deactivation	0.35	2.02	1.84	1.88
Cognitive evaluation	0.69	1.81	1.65	1.77
Satisfaction with travel	0.70	1.99	1.83	1.91
Multi-modal car-commuters (N=375)				
Positive deactivation - negative activation	0.79	2.19	2.06	2.17
Positive activation - negative deactivation	0.23	2.07	1.85	1.94
Cognitive evaluation	0.48	1.84	1.67	1.78
Satisfaction with travel	0.50	2.03	1.86	1.96

As we hypothesize that health status may influence satisfaction with e-cycling, the change in physical health after six months of participation was added as a variable in the model after six months. This variable is a dummy variable indicating whether a participant has a higher self-reported health status after six months as compared to the baseline situation. Table 5 shows the results of the three models.

All models have a very acceptable goodness-of-fit. Overall, the models indicate that the amount of increase in travel satisfaction, which was reported before, is not systematically related to personal characteristics such as age, gender, income or household composition. Notably, whether the respondent occasionally commuted by bicycle before the program does not affect the change in travel satisfaction resulting from the mode shift either. However, individuals' mobility and residential context appears to have an impact. Commuters with one car in the household (as opposed to two or more) experience a larger increase in travel satisfaction one month after entering the program. This may be due to a less car oriented lifestyle, making it easier to appreciate e-cycling. After six months the differences between different levels of car ownership are not significant. In addition urban density has an impact on the change in travel satisfaction. Compared to participants in non-urbanised areas, those in strongly urbanised areas and less urban areas have a lower expectation of satisfaction with e-cycling, and a marginally significant lower satisfaction after six months. Participants in less urban areas also have a lower travel satisfaction after one month. Probably, the higher speed of e-bikes, which is one of their main merits, is less experienced in denser urban areas due to more interaction with other road users.

The change in travel satisfaction is also influenced by current commuting behavior and the commute experience. In particular, those using the e-bike more frequently for commuting have a larger increase in travel satisfaction after one and six months. This points at an clear self-selection effect, in that those with a higher satisfaction also use their e-bike more frequently. In addition, the extent to which car use and e-cycling is experienced as strenuous has strong effects on the increase in travel satisfaction. Logically, those who find car commuting more strenuous start from a lower commute satisfaction, and likely profit more from a shift to e-cycling. This holds for the expected travel satisfaction as well as for the travel satisfaction after one and six months. Likewise, the extent to which e-cycling is expected or experienced to be strenuous, has a negative effect on expected and experienced satisfaction with commuting by e-bike. If one can determine the speed of cycling more autonomously, this will lead to a larger increase in travel satisfaction resulting from the mode shift, both in terms of expected satisfaction and satisfaction after six months. Apparently, as noted in the context of urbanization level, if one can take full profit of the higher speed of e-cycling, this leads to a higher appreciation of e-cycling.

Table 4. Significance of differences between STS for car-commuting (baseline), expected e-cycling (baseline) and experienced e-cycling after one and six months.

Variable	Car baseline vs. E-bike baseline	Car baseline vs. E-bike after 1 month	Car baseline vs. E-bike after 6 months	E-bike baseline vs. E-bike after 1 month	E-bike baseline vs. E-bike after 6 months	E-bike after 1 month vs. E-bike after 6 months
All participants (N=547)						
Positive deactivation - negative activation	**0.000**	**0.000**	**0.000**	**0.000**	0.414	**0.013**
Positive activation - negative deactivation	**0.000**	**0.000**	**0.000**	**0.000**	**0.001**	0.056
Cognitive evaluation	**0.000**	**0.000**	**0.000**	**0.000**	0.290	**0.010**
Satisfaction with travel	**0.000**	**0.000**	**0.000**	**0.000**	**0.046**	**0.006**
Only car-commuters (N=172)						
Positive deactivation - negative activation	**0.000**	**0.000**	**0.000**	**0.033**	0.470	0.262
Positive activation - negative deactivation	**0.000**	**0.000**	**0.000**	**0.003**	**0.042**	0.483
Cognitive evaluation	**0.000**	**0.000**	**0.000**	**0.047**	0.662	0.131
Satisfaction with travel	**0.000**	**0.000**	**0.000**	**0.005**	0.233	0.177
Multi-modal car-commuters (N=375)						
Positive deactivation - negative activation	**0.000**	**0.000**	**0.000**	**0.005**	0.617	**0.025**
Positive activation - negative deactivation	**0.000**	**0.000**	**0.000**	**0.000**	**0.009**	0.071
Cognitive evaluation	**0.000**	**0.000**	**0.000**	**0.002**	0.325	**0.038**
Satisfaction with travel	**0.000**	**0.000**	**0.000**	**0.000**	0.110	**0.016**

Table 5. Regression analysis of expected and experienced change in STS when shifting from car to e-bike.

	Car baseline > E-bike baseline		**Car baseline > E-bike after one month**		**Car baseline > E-bike after six months**	
	B	sig.	B	sig.	B	sig.
(Constant)	0.644	0.173	-0.254	0.659	-0.676	0.197
25-39 years	0.007	0.963	-0.074	0.639	0.085	0.578
40-49 years	0.110	0.302	0.127	0.272	0.020	0.858
50-65 years	-	-	-	-	-	-
Male	-0.034	0.750	-0.147	0.202	-0.087	0.428
Female	-	-	-	-	-	-
Phys. cond. bad	-0.276	0.080	-0.339	0.053	-0.160	0.349
Phys. cond. neutral	-0.200	0.127	-0.035	0.806	-0.067	0.629
Phys. cond. good	-0.150	0.166	-0.086	0.470	0.003	0.982
Phys. Cond. excellent	-	-	-	-	-	-
1 car per household	0.132	0.158	0.210	**0.038**	0.145	0.134
2+ cars per household	-	-	-	-	-	-
< 3.000	-0.045	0.691	-0.083	0.494	-0.123	0.294
3.000 - < 4.000	0.075	0.500	-0.056	0.644	-0.049	0.673
> 4.000	-	-	-	-	-	-
Single	0.266	0.216	-0.289	0.227	0.017	0.938
Single parents	-0.102	0.745	-0.099	0.773	-0.109	0.739
Couples without children	-0.316	0.145	0.189	0.426	-0.227	0.315
Couples with children	-	-	-	-	-	-
(very) Strong Urbanized	-0.298	**0.040**	-0.177	0.261	-0.262	0.082
Moderate urbanized	-0.071	0.572	-0.146	0.293	-0.102	0.443
Less urban urbanized	-0.258	**0.023**	-0.265	**0.032**	-0.202	0.089
Not Urbanized	-	-	-	-	-	-
0-5 km	-0.127	0.633	-0.538	0.065	-0.343	0.228
5<10 km	-0.169	0.286	-0.281	0.113	-0.121	0.471
10<15 km	-0.095	0.482	-0.172	0.250	-0.003	0.983
15<20 km	-0.196	0.144	-0.248	0.091	-0.099	0.485
20+ km	-	-	-	-	-	-
1-3 days a week	0.142	0.349	-0.005	0.978	0.066	0.677
4 days a week	0.077	0.458	0.232	**0.040**	0.167	0.125
5 days a week	-	-	-	-	-	-
Conventional cycle share at baseline	0.292	0.136	0.213	0.335	0.269	0.195
E-cycle share	-	-	0.872	**0.000**	0.874	**0.000**
Strenuous car commute	0.432	**0.000**	0.439	**0.000**	0.379	**0.000**
Strenuous E-cycling commute	-0.159	**0.000**	-0.120	**0.001**	-0.129	**0.000**
Crowdedness during commute	-0.042	0.251	-0.042	0.347	-0.038	0.404
Freedom of speed determination	0.141	**0.000**	0.083	0.068	0.103	0.022
Annoyed by road users	-0.056	0.184	-0.011	0.789	-0.022	0.616
Threatened/Unsafe by road users	0.012	0.775	0.019	0.683	0.013	0.794
Route unsafety	-0.022	0.616	-0.029	0.580	-0.037	0.493
Wayfinding	-0.043	0.458	-0.124	0.092	-0.115	0.104
Distraction by billboards	-0.029	0.501	-0.028	0.608	0.019	0.729
Green	-0.010	0.811	0.069	0.209	0.154	**0.002**
Openness	0.061	0.069	0.041	0.298	-0.018	0.629
Aesthetics	-0.056	0.278	-0.005	0.924	0.082	0.172
Liveliness	-0.052	0.317	-0.001	0.988	-0.040	0.464
Atmosphere	-0.075	0.208	-0.157	**0.012**	-0.054	0.381
Height difference	0.018	0.508	0.019	0.562	0.028	0.375
Landscape	0.007	0.862	0.003	0.952	-0.077	0.066
Urbanization	0.111	**0.006**	0.059	0.184	0.053	0.238
Reported change in health status	0.144	**0.003**	0.140	**0.008**	0.191	**0.000**
Share of car-commuting at baseline	0.000	0.999	0.063	0.670	0.019	0.895
Adjusted R-square	0.407		0.408		0.398	

Finally, the landscape through which one cycles has impact on the increase in travel satisfaction. A greener landscape leads to a larger increase in travel satisfaction after six months. A less cosy landscape leads a smaller increase after one month, and a more urbanised landscape leads to a higher expected increase in travel satisfaction. The latter is in contrast with the effect of urbanization level noted before, but it should be noted that this variable concerns the perceived urbanization of the commute route, which may differ from the urbanization level of the residence. Finally, although health status itself does not impact on the increase in travel satisfaction, improvement of health status does have an effect. Apparently, the experience of improved health as a result of e-cycling has a positive effect on travel satisfaction.

5.5 Discussion

This paper reported on the effects of an e-cycling stimulation program on travel satisfaction in the province of Noord-Brabant, the Netherlands. The program was designed to stimulate car-commuters to use their e-bike in daily commuting, earning monetary incentives for each kilometre participants e-cycled. With a longitudinal design this study allowed to observe changes in behavioral and travel satisfaction.

Our study did find support for the hypothesis that the travel satisfaction with e-cycling is higher than for car-commuting. With an increase of about 1.4. on a 7-point scale, this suggests that a shift from car to e-bike generates a considerable increase in commute satisfaction, and therefore possibly in overall well-being. Notably, a similar increase was observed for commuters who only used the car before the programme and those who occasionally used the bicycle. This implies a high and intrinsic travel satisfaction with e-cycling among participants, that is not dependent on cycling experience. Motivational theories of behavior change, such as Self Determination Theory (SDT) (Standage and Ryan, 2012) posit that changes in behavior are more likely to be sustained if individuals find the new behavior more pleasant and therefore develop an intrinsic motivation to perform it. In that sense, our results suggest that e-cycling might be sustained on the longer run. Of course, this requires that travel satisfaction remains at the similar high level as at the one-month and six-month measurement, which should be investigated in follow up studies.

We find that the initially experienced satisfaction with e-cycling is slightly lower than the expected satisfaction. This suggests that both the focussing illusion and a forecasting bias might be present: participants slightly overestimate the positive aspects of e-cycling. However, initial satisfaction with e-cycling is still high. Where some well-being literature indicates a hedonic treadmill effect, our study finds that travel satisfaction remains high for a period up to six months, and actually slightly increases. Apparently, the habituation to e-cycling causes an increase of travel satisfaction over time. Interestingly, the negative impact of physical condition diminishes over time, suggesting that improved health as a result of e-cycling might be a reason for the slightly increased satisfaction. Again, this adds to the attractiveness of e-cycling in the long term. With respect to the health effects, we note that although the e-bike has technical advantages over the conventional bicycle regarding speed and action radius, e-cyclists still have to deliver substantial physical effort (Simons et al., 2009) which enhances health and reduces the chance of sedentary lifestyle diseases (De Geus et al., 2013). In addition, our study finds that the attractiveness of the route influences travel satisfaction. Factors like greenness and liveliness of the environment contribute to a positive travel satisfaction. In this respect, e-cycling resembles conventional cycling. However, there are also indications that factors that are specific for e-cycling such as autonomy in choosing one's speed influence travel satisfaction, leading to preferences for less urbanized areas to e-cycle.

Of course, this study is subject to limitations. One limitation concerns the setting of the e-cycling stimulation program, mainly focussing on commute travel. It remains uncertain to what extent trips for different travel purposes made by e-bike would have similar travel satisfaction. The use of e-bikes for recreation purposes may imply different requirements to infrastructure and cycling environment, resulting in different levels of satisfaction. In addition, although the results are promising in terms of the increase in travel satisfaction, it remains questionable to what extent satisfaction with e-cycling will remain high in the longer term, and whether the modal shift from car to e-bike will last after the program ended. Another limitation concerns the way in which commuters were persuaded to start the use of the e-bike in this study, based on monetary incentives. It is unclear if commuters who take up e-cycling independently (i.e. without a stimulation programme) will experience a similar increase in travel satisfaction, as their characteristics and the social context may be different, as well as their motivations to e-cycle. In addition, the fact that a monetary incentive is earned for e-cycling may affect the satisfaction with e-cycling. In the current study we could not disentangle these effects, as satisfaction was only measured during the program, when the incentive was received. It is therefore recommended that future studies address satisfaction with e-cycling in other contexts.

This study is a first step to investigate the potential of e-cycling in commute travel. More research is needed to fully understand the shift to e-cycling and its implications. Firstly, the shift towards the e-bike in daily commuting was induced by monetary incentives as part of a regional mobility program. It cannot be concluded that similar effects in size can be expected in other contexts (e.g., in different geographical contexts or without providing incentives) nor that responses are subject to the same influential factors. More studies of e-bike adoption with a longitudinal character in a variety of contexts are required to answer these questions. Secondly, the quality of cycling infrastructure was not taken into account explicitly, where the Dutch context generally caters for high quality cycle infrastructure. These characteristics may differ strongly between for instance the Netherlands, with an extensive cycling infrastructure, and North-American settings where such infrastructure is often lacking. Next to questionnaires, route characteristics could be based on available GPS-data from the participants commute trips, augmented with detailed information about spatial and natural context. Thirdly, it makes sense to study behavioral change and travel satisfaction over a longer period, than in the current study, to find out if a sustained high level of travel satisfaction indeed leads to sustain e-cycling behavior, as discussed before. Adherence to e-cycling as healthy behavior is a crucial factor for sustained positive health effects. Studies in other domains (Ettema et al., 2010) have shown behavioral change brought about by incentive programs not to be necessarily sustained when the incentive ends.

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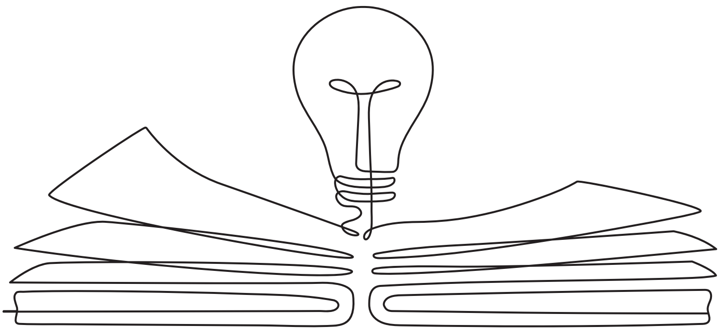
CHAPTER 6

Conclusions, discussion and policy recommendations



6.1 Introduction

With the technical advantages of higher speeds and the reduction in physical efforts due to the electric pedal assistance, the e-bike (Fishman and Cherry, 2016) is regarded as one of the sustainable alternatives for short and particularly midrange distances (< 15 km) for the predominantly car-oriented lifestyle among many populations in the Netherlands. Although the Netherlands is known for its cycling culture, high bicycle occupation rates, and high-quality cycling infrastructure, the car is still dominant with 69% (CBS, 2022) of daily traveled km by car. From a sustainability and policy perspective, the substitution of car trips during peak travel hours by e-bike leads to a reduction in congestion and therefore contributes to the economic accessibility. The assumption is that the e-bike potentially mitigates the unattractiveness of utilitarian conventional cycling for longer distances. This difference is important since various studies have shown that people who live close to their workplaces (< 5 km) are already significantly more likely to use conventional bicycles to commute than those with longer commutes (Kingham et al., 2001; Dickinson et al., 2003; Krizek et al., 2010). In addition, the substitution from car to e-bike alleviates the negative environmental impact caused by car use and contributes positively to causing an increase in physical activity ((Akar and Clifton, 2009; Badland and Schofield, 2008; Sugiyama et al., 2008).

Over the last decade extensive research has been conducted concerning e-cycling ranging from technical advantages, impact on cycling safety, and sociodemographic and household characteristics of conventional and e-cyclists, in addition to cyclists' behavioral change (Fishman and Cherry, 2016; Plazier et al., 2017; Kroesen, 2017). Prior to the start of this research, studies supporting transportation policy regarding behavioral changes had been cross-sectional in nature. This thesis adds to this knowledge by examining longitudinal effects in the context of e-cycling incentive programs such as behavioral change over time and adherence, existence and development of intention-behavior gap, day-to-day e-bike use in relation to weather dynamics, and dynamics in e-cycling appreciation. This is important to understand underlying mechanisms for lasting behavioral change towards e-cycling.

In general, behavioral intention is often explained by belief-related variables, such as attitude, subjective norms, and perceived behavioral control based on the TPB (Ajzen, 1991) in conjunction with past behaviors and/or habits (Gardner and Rebar, 2019a). Because the intended behavioral changes within the incentive program were specifically aimed at going to work via e-bike, goal-related variables, such as goal-perceived feasibility, goal desire, and goal-anticipated emotions from the EMGB (Perugini and Conner, 2000) were used in this study. Over time, participants in the program changed their commuting behavior toward e-cycling to some extent and developed new commute experiences that potentially can also cause changes in behavioral intentions. The longitudinal setup of the study enabled us to better understand both the intention to change, the behavioral change itself, and the intention-behavior gap over time.

Next, the longitudinal approach enabled us to explore the impact of various weather circumstances on the use of the e-bike. Existing research on the impact of adverse weather condition on conventional cycling (Böcker et al., 2019; Böcker and Thorsson, 2014) shows that the effects of air temperature, amount of precipitation, strong winds, and presence of snow and ice on the infrastructure affects the use of the conventional bicycle. Furthermore, the longitudinal approach enabled us to explore dynamics in the attractiveness and appreciation of e-cycling which is determined at least partially by an individual's satisfaction with travel. Existing research shows that conventional cycling already is associated with higher travel satisfaction as compared to motorized travel modes (Olsson et al., 2013; Mao et al., 2016; St-Louis et al, 2014; De Vos et al., 2015). The technical advantages of the e-bike might affect the choice of taking the e-bike to work under varying weather conditions and the satisfaction with such travel.

The central question of this thesis is:
What are the effects of an e-cycling incentive program on short and longer term behavioral change, how can these outcomes be understood from underlying behavioral processes and external factors, and how does the changed behavior lead to changes in travel satisfaction?

In the following sections, the main answers of the thesis are discussed following the four sub-questions and main research questions presented in the introductory chapter. Next, the theoretical implications, the main limitations, and future research in addition to the policy implications of this study are discussed.

6.2 Answer to research questions

6.2.1 Behavioral changes

In chapter two, exploring the impact of sociodemographic characteristics, spatial attributes, commuting behaviors, and satisfaction with car travel in relation to the shift to e-cycling was the main aim. As such, chapter two dealt with the first sub-question, which asks:

What is the effect of e-bike introduction on daily commuting in terms of modal shift and persistence in behavioral change?

As the e-bike is regarded as a sustainable alternative to car commuting for short and midrange distances (< 15 km), the first article focuses on the actual behavioral change brought about by the incentive program on the e-bike in daily commuting patterns.

With an overall modal shift to two-third of all commuting trips using the e-bike after a month of participation, the program appears to have had a substantial impact on behavioral changes among participants. Next to the substitution effects towards e-bike use, the habitual mode choices over the week prior to the program are interesting too. To better understand the actual changes, descriptive analyses related to baseline mode choices show that e-bikes substituted for both car and conventional cycling to about the same extent. With an incentive program targeted at car commute trip substitution by actively stimulating e-bike use, the almost complete substitution of baseline conventional cycling was unexpected but remains nevertheless positive in terms of stimulating active travel. This outcome is confirmed by other research showing that e-bike ownership also substitutes for conventional bicycle ownership and bicycle use more than car and public transport use (Kroesen, 2017). Of course, substitution of conventional cycling mainly takes places for shorter distances, whereas longer distances using an e-bike is a substitute for car trips. After one month, for short-range distances up to 10 km, 75% of all commuting trips were made by e-bike of which 53% originally were car commuting trips, and 43% were conventional cycling. For the distance range between 10 and 20 km, 67% of all commuter trips were made by e-bike of which 62% were initial car trips and 33% conventional cycling. For cycling distance over 20 km, the e-bike share was 63% of all trips with an initial 72% car trips and 21% conventional cycling.

After an initial introduction to e-cycling to work within the first month, the behavioral changes might have been attenuated, whereas the opposite effect was found in the program. Linear regression shows that improved subjective physical health status has a positive effect on the use of the e-bike over time. Half a year after enrollment in the program, car use among participants dropped below 25% of all commuting trips for which the increase in e-cycling was shown to be in the distance range of 0 to 10 km and up to 81% (+6%) and 72% (+5%) in the distance range of 10 to 20 km. Therefore, the distinction in commuting distance classes is important in which baseline car shares are larger for the longer distances, and more substitution by e-bike for the car occurs for those distances.

Regression analyses show that the use of the conventional bicycle for commuting in the baseline situation plays an important role in potential e-bicycle usage. To better understand the potential impact on the conventional cycling experience, a distinction is made between participants with and without habitual cycling experience while commuting. Based on linear regression modeling, both groups show differences in behavioral changes related to commuting distances for which most persistent substitutes take place in terms of home-work distances that are between 0 and 20 km. Especially, the group of participants who only used the car prior to the program shows the largest decrease in car use over time of 30%

on 5 to 15 km distances and 40% on distances over 15 km. The distinction in level of cycling experience is in line with existing research concerning conventional cycling (Gatersleben and Appleton, 2007)

In line with existing research on physical limitations as negative effects on cycling (Popovich et al., 2014, MacArthur et al., 2014), bad physical health conditions have been shown to significantly affect e-cycling. Remarkably, this effect is weaker in effect size and significance after participating half a year in the program. We consider that this may be because participants' health improves due to the shift to e-cycling from other modes of transportation. In addition, gender, car ownership, and household composition influence the modal shift on individual and household characteristic levels. Previous research on conventional cycling (Heinen et al., 2010) showed that spatial context, natural context, and the constructed environment influence the choice of the use of a bicycle for daily commuting. Surprisingly, no effects due to the degree of urbanization (of the home location) was found in this study. More recent research on e-cycling supports the findings that because of the electric pedal support of the e-bike, restrictions on ranges and physical efforts (Plazier et al., 2017), which are the main barriers to conventional bicycle use in daily commuting, are mitigated (Heinen et al., 2010; Heinen and Handy, 2012).

6.2.2 Behavioral intentions, changes, and intention-behavior consistency

Since the e-cycling incentive program in general is targeted on the shift to e-bikes with the aim of reducing car traffic during peak hours, the behavioral changes of individuals depend on their personal intentions to change and behavioral persistence. Based on this program, this thesis explored the intention and actual behavioral changes brought about by the program. To do so, the following research question was formulated:

To what extent do participants adjust their behavioral intention to use the e-bike in daily commuting and changes the intention-behavior gap over time?

The second article focuses on potential changes in behavioral intention and the actual behavioral change. First, descriptive analyses show the development in e-cycling intention over time for which it may be assumed that expectations and intentions become more realistic after one month of participation in the program. Overall, two-thirds of all participants did not change their intentions over the duration of the whole program. Participants without conventional cycling experience while commuting tended to be a bit less consistent compared to the groups of people used to conventional cycling for two or three days a week in the baseline situation. Apart from the group car-only participants with constant intentions, two-fifth adjusted their intentions downward and three-fifth upward. Within the group of experienced cyclists, the adjusted intentions were limited. Participants cycling four or more days a week in the baseline situation showed an 83% consistency, which can be explained by past experiences with conventional cycling to work.

The longitudinal approach enabled us to analyze relating participants' behavioral intention and actual behavior on an individual level with which the intention-behavior gap over time. During the first month of participation, the consistency between people's stated intention and the actual behavior towards e-cycling was found to be just above 50%. The remaining group of participants showed a large share of people underperforming to their stated intentions (41%) compared to the overperforming group (8%). Apart from a small group without any stated intentions to commute by e-bike, all groups showed a 47%-57% intention-behavior consistency. The group of participants with habitual conventional cycling experience performed better in terms of higher consistency than the baseline car-only commuters. Despite the differences between the experienced and inexperienced commuter cyclists, the intention-behavior consistency remained stable with a 50% average over the first half year of participation. This finding is in line with the studies in which it was reported that the addition of self-determined implementation intentions produced a positive effect on behavioral changes (Reuter et al., 2008; Sniehotta et al., 2005; Wieber et al., 2015). During the program the group of people overperforming on their intentions increased to 21% (+13%), a finding that suggests that people were developing an e-cycling habit. Even though this group was limited in numbers, the underperformance decreased to an average of 29% (−12%). The distinction in level of experience is again in line with previous cycling research in which a distinction was drawn between the experienced cyclists and participants without any or hardly any (one day a week) commute cycling experience (Gatersleben and Appleton, 2007). Also, the conventional cycling habit seems to influence e-cycling intention-behavior consistency.

For situations in which the process of adaptation to e-cycling was compared to other processes in which behavioral changes, such as healthy eating, maintaining a healthy weight, and smoking cessation, were favorable but difficult to accomplish (Faries, 2016), ordinal regression modeling did not show convincing relationship with belief-related variables, such as attitude, subjective norms, and perceived behavioral control from the TPB and additional goal-related variables such as goal anticipated emotions, goal perceived feasibility, and goal desire for the EMGB. It might be speculated that motivation and intentions precede the decision whether (or not) to participate in the program at all. Because e-bike ownership or e-bike acquisition when entering was a boundary condition to enroll in the incentive program, it can be assumed that participants already had a positive mindset towards e-cycling.

6.2.3 Weather conditions

One of the most important environmental factors influencing conventional cycling is the natural environment, specifically the landscape, seasons, climate, and weather conditions (Heinen et al., 2010). Related to daily conventional cycling strong winds, precipitation, and air temperature, the presence of snow and ice affect daily mode choices (Böcker and Thorsson, 2014). The technical advantages of the e-bike might mitigate the negative impact of the natural environment. To address the impact of adverse weather conditions on e-cycling, chapter four addresses the next sub-question:

To what extent do integrated effects of adverse weather conditions, such as impact of precipitation, temperature, and strong winds affect e-bike use in daily commuting?

As adverse weather conditions, such as rain, strong winds, and temperatures, have already been proven to have a negative impact on conventional cycling, the third empirical article specifically focuses on the effect of ranging weather conditions on e-cycling. Combining continuous commuting behavior measured with GPS-data, weather circumstance information from regional weather stations and sociodemographic information of participants on the impact was explored.

During the incentive program, all participants were exposed to various weather conditions ranging from sunny days to adverse weather conditions. During the program, the number of observations of air temperature below 0°C limited causing the analyses to focus on the effects of air temperature, precipitation, and wind speed for which the presence of snow and ice on the infrastructure did not occur often enough to be relevant to the study. Descriptive analyses indicated that air temperatures, wind speeds, and the total amounts of precipitation significantly influenced the probability of e-cycling. Although the Netherlands has a moderate maritime climate with relatively mild winters, mild summers and precipitation throughout the year and relatively high temperatures this affects e-cycling negatively (Böcker et al., 2013a), which is in line with existing research on conventional cycling. E-cycling was found to be significantly affected by strong winds, but the incorporation of stated intention of e-cycling under windy weather conditions did not produce a significant impact on the e-cycling probability, a factor that might have a relationship with the actual increase in comfort of the electric pedal assistances while e-cycling.

Regarding the e-bike as the alternative to car commuting, multivariate regression models show that having the availability of a second car in the household as an alternative mode of transport negatively affected the modal shift to e-cycling because people tended to use the car under adverse weather circumstances. Multiple-person households with only one car available have fewer alternatives in poor weather conditions, and this group was more likely to use the e-bike when it rained or relatively cold weather conditions (< 7 °C) were present more than people having a car alternative. In previous studies, gender was found to be an influential factor for conventional and e-cycling (Fishman and Cherry, 2016; Heinen et al., 2010) on an individual characteristic level. However, this study did not show any significant difference between men and women in households with a certain level of car ownership and the probability that they would use an e-bike to go to work. It might be speculated that this relationship exists because of the specific incentive program and the Dutch context instead of specifically related to e-cycling in general. Although the e-bike mitigates the effects of effort compared to the conventional bicycle and leads to an increase in commuting by e-bike cycling for mid-range distances, adverse weather conditions seem to limit the choice of permanently leaving the car for commuting.

6.2.4 Satisfaction with travel

One of the most important aspects involved in sustainable behavioral changes is the structural effect. Participating in an e-cycling incentive program should accelerate the intended modal shift, where behavioral effects ought to be long lasting. In general, the effectiveness of incentive programs on enhancing sustainable behavior can be questioned (Rau et al., 2022) with the possibility of people reverting back to old behavior. However, because (e-)cycling is a form of active travel, it both affects physical and mental health in a positive manner and therefore leads to an increase in the attractiveness of cycling (Olsson et al., 2013; Mao et al., 2016; St-Louis et al, 2014; De Vos et al., 2015). Because of the potential treadmill effects on the behavioral change process, positive effects on people's mental health could be diminished during the program because people get used to the adjusted behavior and positive the satisfaction over time. To address the effect of e-cycling on travel satisfaction and the longitudinal consistency, the next sub-question was formulated:

What effect does the shift from car commuting to e-cycling have on people's travel satisfaction and how does this develop over time?

The fourth empirical article in this dissertation focuses on the relationship between modal shift toward e-cycling and the satisfaction with travel. Motivational theories of behavior change, such as the Self Determination Theory ([SDT] Standage and Ryan, 2012) suggest that behavioral changes are more likely to be sustained if individuals find the new behavior more pleasant than the old behavior and therefore develop an intrinsic motivation to continue it. Given the longitudinal nature of the study, baseline satisfaction with car commuting, the expected changes, and satisfaction with e-cycling over time were measured to indicate the relative attractiveness or pleasantness of e-cycling.

On average, participants in the program started with a positive level of satisfaction with car commuting. Again, a distinction is being made between satisfaction with travel of participants with and without conventional cycling commute experience. Descriptive analyses shows that participants who were used to taking the car only to commute were slightly more satisfied with the use of the car than people used the conventional bicycle to go to work. However, both groups had approximately the same expected satisfaction with e-cycling at the start of the incentive program in which the stated satisfaction with e-cycling was significantly higher than with car commuting. Compared to the expected satisfaction at the start, the level of satisfaction with e-cycling after one month participating in the program was somewhat lower than estimated by participants but still significantly higher than the level of satisfaction with car commuting. Similar effects involving positive levels of satisfaction with e-cycling were shown after six months of participation, which entails no significant impact of potential treadmill effects. Especially for the group of participants with limited or without any conventional commute cycling experience, the e-bike use was higher during the program, which might have led to a positive level of satisfaction with their e-cycling trips.

Compared to previous cross-sectional studies involving travel satisfaction (Olsson et al., 2013), descriptive analyses showed a significant increase in satisfaction. For all participants, the level of satisfaction with e-cycling was somewhat lower than expected but still much larger than the level of satisfaction with the car. However, linear regression models indicate that the increase in travel satisfaction for commuting by e-bike was not systematically related to personal and most household characteristics. Commuters with only one car in the household experienced a larger increase in satisfaction levels as opposed to those commuters having two or more cars. Over time, this effect was attenuated somewhat for both groups of car owners.

The spatial context in general and the urban density specifically appear to have a significant impact on the changes in travel satisfaction. People from strongly urbanized areas and less urban areas have a lower expected level of travel satisfaction with the e-bike than participants in non-urbanized areas. The higher speeds of the e-bike as one of its main benefits, is less advantageous in denser urban areas due to more interactions with other road users. In addition, the greenness and liveliness of the environment through which one cycles (in line with conventional cycling literature) has a positive impact on the increase in level of travel satisfaction. However, indications that factors that are specific for e-cycling, such as autonomy in choosing one’s speed influence travel satisfaction, also lead to preferences for less urbanized areas to e-cycle.

Although the perceived physical health status does not directly influence travel satisfaction, the experience of improved health resulting from e-cycling has a positive effect on travel satisfaction. Interestingly, the negative impact of poor physical condition diminishes over time, suggesting that improved health because of e-cycling might be a reason for the slightly increased satisfaction. E-cyclists must still exert substantial physical efforts (Simons, Van Es, and Hendriksen, 2009), which leads to an enhancement in health status and reduction in the chance of sedentary lifestyle diseases (De Geus et al., 2013). Overall, it can be argued that the increase in physical health over time and the positive satisfaction with e-cycling contribute to its attractiveness and therefore contributes to behavioral changes instead of the other way around.

6.3 Theoretical implications

This thesis generated theoretical implications on four levels. First, implications for understanding of the impact that incentive programs have on behavioral changes of different user groups were examined. Second, implications for insights into the efficiency of the concrete incentivization approach on individuals' behavioral changes and levels of satisfaction with travel are suggested. Third, implications for the body of existing research on a cross-sectional basis about the changes in behavioral intention, actual behavior, and intention-behavior consistency over time are present. Finally, implications for understanding which role belief- and goal-related variables play in the behavioral change within existing incentive programs are discussed.

The impacts of the incentive program on behavioral change of different user groups

This thesis provides the basis for a better understanding of the longitudinal impact of an incentive program on behavioral changes toward e-bike use for daily commuting for different user groups. In contrast to various e-cycling related studies (see Fyhri and Sundfør, 2020; Sun et al., 2020), the incentive program analyzed in this thesis was targeted at breaking habits (Gardner and Rebar, 2019), stimulating pursued behaviors, and gradually routinizing e-bike use through repetition. In general, the incentive program was effective in terms of behavioral changes over time in which participants kept using the e-bike for daily commuting over a period of time. In addition, a distinction is found between user groups with respect to both commute distances and prior experience with conventional cycling to work. Building on existing literature on cycling in general (see Gatersleben and Appleton, 2007), this distinction suggests that the substitution effect toward e-bike use is dependent on people's travel distances, past cycling experiences, and design of the incentive program itself. Several intervention programs have shown promising effects on behavioral change, but it remains unclear whether such a program offers a route to long-lasting behavioral changes (Gardner and Rebar, 2019). In addition, various studies have shown that e-bike ownership itself results in substitution with other modes of transport, such as public transport and car use (Kroesen, 2017; Plazier et al., 2017). However, the effectiveness of incentive programs targeted at stimulating e-bike ownership on longer term behavioral changes remains unclear (see Fyhri and Sundfør, 2020; Sun et al., 2020). In addition, cycling distances were shown to affect the modal shift toward e-bike use. Previous research on conventional cycling (see Heinen et al., 2010) suggests that the substitution effects of car use toward conventional cycling were rather limited because of the increase in physical effort. In this thesis, the substitutional effects on the shorter-range home-work distances (< 7.5 km) were found to be mostly from conventional cycling toward e-bike use for which the actual pursued substitutional effect from car toward the use of e-bike takes place at the longer distances (7.5 < km < 20 km). Hence, modal shift effects that occur from the e-bike incentive program are distance-dependent.

This study also confirms previous research findings (see Gatersleben and Appleton, 2007) on the impact of differences in cycling experiences or past cycling behaviors. In general, this study implies that stimulating e-bike use by monetary compensation is an effective intervention in terms of behavioral changes toward e-bike use over time. More specifically, it implies that stimulating behavior itself instead of e-bike ownership is an effective strategy for facilitating long-term sustained behavioral changes. The study also implies that next to the actual modal choice, the modal shift is equally important in program evaluations. Therefore, when analyzing modal shift effects, the initial travel mode should be considered more specifically. For instance, specific actions can be taken to target people traveling the mid-range and longer cycling distances to work for which it would be more likely that car use is more likely substituted for cycling modes. In addition, specific attention should be paid to people with less cycling experience to achieve substitution for car travel. Since this thesis contributes to understanding the effects of behavioral interventions and the specific role of distance in a specific Dutch geographical context, additional longitudinal research could be used to explore effects of other natural geographic barriers, such as hills, different international contexts, and cycling cultures.

Behavioral change and satisfaction with travel

This thesis measured e-bike use, travel satisfaction levels, and self-reported health longitudinally over six months. A general finding is that the incentives on e-bike use work well to help participants shift from car commuting to commuting by e-bike but also to make this a sustained change during the research period. In addition, it was found that an increase takes place in levels of travel satisfaction when shifting to the e-bike, which was maintained throughout the research period. Also, on average, an increase in self-reported health status was observed by the end of the research period. Taken together, and building on an emergent literature (De Vos, 2019; De Vos et al., 2020) this suggests that travel behavior, travel satisfaction and health may be mutually related and reinforce each other. For instance, Van Wee and Ettema (2016) reported evidence that the relationship between subjective well-being (including travel satisfaction) and physical activity (such as active travel) may be bi-directional. Similar findings have been reported by De Vos. Hence, the shift to e-bike increased travel satisfaction, it is conceivable that increased satisfaction also led to an increase in the probability that participants continue e-biking. Likewise, the positive health effects of cycling (including e-biking) have been extensively reported. However, it was also found that someone's health status has an impact on the probability of cycling (ref) but also that the experience of active travel (and physical activity in general) depends on one's physical health. This finding suggests that if physical health improves through cycling, this event itself produces an improvement in the probability that cycling is maintained. The results of this study as mentioned above support the existence of positive feedback loops between e-biking, travel satisfaction, and physical health. This finding implies that all three aspects (behavior, satisfaction, and health) need to be considered when developing interventions to stimulate active travel. For instance, specific actions can be taken to improve levels of travel satisfaction by giving advice about possible attractive routes or organizing parking facilities properly. Also, specific attention should be paid to participants for whom their health status may make cycling less attractive. However, this decision should rest on additional longitudinal research into the mutual relationships between these factors.

Intention-behavior consistency over time

Using a longitudinal approach, this thesis not only measured the changes in behavioral intention on a cross-sectional basis but also reported changes in actual behavior and intention-behavior consistency over time. Both intentions and behaviors were shown to be rather consistent during the six-month period investigated in this thesis. This finding suggests that people who enroll in a large-scale structured incentive program have a strong motivation for making behavioral changes toward e-bike use mostly implement their intentions as intended and persevere over time. These results add to the existing body of literature about evaluating cycling-related interventions with a shorter duration (Abou-Zeid et al., 2012; Plazier et al., 2017) or on stimulation of e-bike ownership (see Fyhri and Sundfør, 2020; Sun et al., 2020). In this study, having an available e-bike and defining the intention to go to work via e-bike on a set number of days per week, the implementation toward e-cycling pointed in the same direction over time. However, various studies have reported inconsistencies between behavioral intention; thus, the actual implementation and persistency may be prevented (Sniehotta et al., 2005). In fact, research concerning public health has suggested that intention is a poor predictor for behavioral change (Faries, 2016; Grimmer & Woolley, 2014). Adaptation of behavior in favor of a healthy lifestyle based on healthy eating, smoking cessation, and increasing the amount of exercise to reduce weight has shown to be difficult. While the implementation of intentions is successful sometimes, persistence has shown to be a challenge. This thesis suggests that once people have enrolled in a structured large-scale incentive program in which they already have made a financial investment, the probability that behavioral intention is implemented and maintained will improve. This finding implies that better understanding should be developed concerning the differences between factors influencing behavioral intentions, implementation, and intention-behavior persistency with and without a personal financial investment prior to the start of the program. In particular, this study suggests that specific attention should be paid to participants' motivation to participate and willingness to change behaviors during the recruitment process and the role that selection of participants (via a necessary financial investment) plays in the success of incentive programs.

Role of belief and goal related variables in behavioral change

This thesis measured the influence of belief-related variables (Ajzen, 1991), goal-related variables, (Perugini and Conner, 2000) and past behaviors and habits (Gardner and Rebar, 2019) on the behavioral intention and actual change toward e-bike use. This thesis did not find support that belief-related variables, such as subjective norms, attitudes, perceived behavioral control, and goal-related variables, such as goal intentions, goal-perceived feasibility, and anticipated emotions, significantly influence behavioral intention and/or implementation of e-bike use. However, past behavior and specifically the use of the conventional bicycle to go to work has been shown to influence the behavioral change towards e-cycling positively. This finding suggests that the influence of belief- and goal-related variables on behavioral changes is dependent on the specific context. In addition, this concept suggests that behavioral change strategies focusing on belief- and goal-related variables do not influence behavioral changes in people with an already positive motivation toward specific behavior, such as in this study, that of e-bike use. It can be hypothesized that the necessary financial investment prior to the start of the program sorts out the more motivated participants with a more positive beliefs about e-bike use, making beliefs and motivations a less important factor. In addition, the strong drive provided by the financial incentive for e-bike use will make this factor a stronger determinant than motivations and beliefs. Therefore, this study supports existing literature (Fyhre et al. 2017) in which subjective norms and attitudes toward cycling did not predict changes in intentions to use an e-bike.

In addition, the potential influence of people who are important to a participant or subjective norm discouraging people to participate are outside the scope of the E-Riders program. Therefore, this thesis does not suggest that behavioral encouragement by people, such as family, friends, and co-workers, who are important to someone do not affect people's decisions to engage in behavioral change processes. Also, this thesis does not suggest that encouragement strategies affecting subjective norms, personal attitudes, or goal perceived feasibility do not influence the performance of participants within an incentive program. However, this thesis implies that to use behavioral theories in general and explore the influence of belief- and goal-related variables, specific program context and conditions should be considered. For instance, specific attention should be given to the general societal motivation toward sustainable behavior and people who enroll into such programs. More specifically, employees living at a mid-range cyclable distance from home can be questioned for future research on their potential motivation to start using an e-bike to go to work taking subjective norms, perceived behavioral control, attitudes, and habits in addition to goal feasibility and goal-anticipated emotions into account to determine the potential influence of belief- or goal-related behavioral encouragement toward sustainable behavior, such as e-cycling.

6.4 Limitations

This study on the effects brought about by a large-scale e-cycling incentive program presents new, empirically-based insights into the way people intend and actually change their behavior toward e-cycling for daily commuting. However, this dissertation also has limitations, which may have influenced the findings and which call for additional research.

The first limitation is related to the selected group of participants in the incentive program who were not selected randomly. Although people were recruited to join the program voluntarily using newspapers and online social media, one of the boundary conditions was having an e-bike at the start of the program. Therefore, participating in the program automatically entails the purchase of a rather expensive e-bike, and thoroughly thinking about perceived behavioral control and willingness to participate are likely to be considered prior the enrollment in the program. It remains unclear to what extent the attitude towards e-cycling, perceived behavioral control, behavioral intention, and other parameters differ from regular e-bike purchasers. Overall, various studies indicate that e-bikes seem to have a special appeal to early users (Wolf and Seebauer, 2014). Therefore, it remains unclear whether the motivation to use an e-bike is the same among participants receiving monetary incentives as among regular e-bike purchasers (see Fyhri and Sundfør, 2020; Sun et al., 2020). Although the results of the incentive program are shown in terms of behavioral changes, the question as to which factors, such as the impact of social pressure from people important to the participants, influence the decision to enroll in a large-scale e-cycling incentive program for a random group of potential participants remains. Answering this question would help target the specific groups of people with belief- and goal-related aims to join.

The second limitation is the program conditions, which did not allow us to reach out to participants after terminating participation in the program due to privacy concerns. The decision to terminate participation by an individual could have occurred during the year prior to the end date, at point of reaching the maximum compensation of €1,000, or after the end date of the program. For all situations, it remains unclear to what extent behavioral changes towards e-cycling in daily commuting were perpetuated. While the program was targeted at behavioral changes brought about by offering people a monetary incentive for e-cycling, the question remains as to what happened if the incentive ended. For the group dropping out at an early stage of the program, it would have been interesting to determine factors influencing their choice to leave the program. In general, an additional question could be raised as to what effect the compensation had on behavioral changes.

The third limitation is related to data collection, some of which took place in 2013 and 2014. Existing research shows that the e-bike suffers from a negative societal image among groups in society (Behrendt, 2017; Boland, 2019; Jones et al., 2016; Leger et al., 2019; Paetz et al., 2012). Although the e-bike has gradually became more mainstream in the Netherlands, over the last decade, the technical evolution of the e-bike and its' appearance has changed. During the pandemic, e-bike sales have skyrocketed with more than half of the bikes being sold in the Netherlands included pedal assistance. This finding indicates that the social and cultural norms related to the e-bike changed among groups in society over time as these parameters were regarded as a barrier to e-bike ownership and e-bike use (Haustein et al., 2020). It remains unclear whether this finding holds for specific groups in society or for society as a whole. Since this research reports on the longitudinal behavioral changes toward the use of the e-bike, the impact of weather circumstances, and effects on people's travel satisfaction, it can be questioned to what extent results would show similar effects nowadays.

6.5 Policy implications

This thesis examined the effects introduced by a large-scale e-cycling incentive program on sustainable behavioral changes. This section provides suggestions on how the findings from this thesis can be translated into mobility policy with the objective to encourage sustainable behaviors, such as e-cycling. The results from this study should also motivate policy makers to shift to a more user-oriented cycling policy development. Based on this study, five implications can contribute to more pro-environmental travel behavior and specifically e-cycling:

- Incentivizing a shift toward e-cycling
- Identifying potential user groups
- Encouraging behavioral persistence
- Understanding e-cycling in a broader policy perspective
- Considering spatial, cultural, and societal context

Incentivizing a shift towards e-cycling

From a policy perspective, the B-Riders e-cycling incentive program is regarded as successful because out of the number of participants who enrolled and started to use the e-bike for one or more days a week to commute, the majority persevered for the duration of the program. While various studies provide insights into the effects of stimulating e-bike purchase or ownership, the outcomes of this study show that stimulating e-bike use results in behavioral changes toward commuting via e-cycling over time. Building on these insights, future incentive programs could be tailored to five aspects:

1. target longer cycle distances.
2. amount of monetary compensation.
3. include social feedback to participants.
4. adjust employers working conditions.
5. encourage e-bike purchase.

The first suggestion relates to the extended cycling range of the e-bike for which incentive programs aimed at e-bike use to alleviate car use could more specifically be targeted toward people living within the mid-range distances from work. This study shows substitutional effects on short distances (< 5 km), which mainly enabled a shift from conventional bicycle to e-bike usage. Although in terms of this particular substitution effect remaining a form of active travel and its positive effects on people's physical and mental health, its contribution to producing a decrease in car congestion at the mid-range distances is rather limited. In the setup of the incentive program, fixed monetary incentives per km were determined for on- and off-peak e-cycling. Despite the policy success of the program, questions remain about the impact of variations in the amount of monetary incentives and duration of the program on achievement of lasting effects. The second suggestion is to monitor and evaluate the amount of the monetary compensation per km. As the incentive program was targeted on stimulating the use of the e-bike to go to work, the amount of monetary compensation per km in the program was established based on the total amount of money available within the incentive program, the assumed average commute distance, the maximum allowed amount of 1,000 (one thousand) euros compensation per participant by the ministry, and the estimated number of potential participants. The relationship between stimulating e-cycling performance over time and flexibility in amount of compensation per km remains an interesting factor to explore in future incentive programs. An increase in compensation per km could positively influence e-bike use, whereas despite a decrease in compensation, people would remain using the e-bike to go to work. The third suggestion for future incentive programs is to introduce alternative incentives based on e-cycling performance to encourage a modal shift toward e-cycling. Over time, various hybrid incentive programs (B-Riders phase II, RingRing, GoVelo) have been developed using monetary incentives for e-bike use combined or based on social incentives. These social incentives contain feedback on personal e-cycling performance, such as total distance cycled, cycling to the destination expressed in km, and amount of CO_2 decrease. In addition to the social feedback on an individual level from the program, social incentives were also introduced at a group level through the activation of employees to cycle as a team, a process that is related to the encouragement of the subjective norms within the company by fellow workers. This latter parameter is related to the fourth suggestion in which employers could be involved in stimulating their employees to use e-cycling. In this particular study, people were recruited using newspapers and online social media. Based on the outcomes of the incentive program, new evidence-based arguments about the positive impact of the modal shift toward e-bike in relation to the travel satisfaction were developed. Employees living at mid-range distances could actively be informed and activated by the employer to take up e-cycling. In addition, employers could offer tax benefits to the cyclists when they purchased an e-bike, mileage allowances, charging stations for e-bikes, leasing e-bike, showers at work, and appropriate bicycle parking facilities. Finally, the suggestion for policy makers is to support employers in adjusting working conditions by broadening tax legislation for companies to stimulate the purchase of the relatively expensive e-bike.

Identifying potential user groups

This research provides comprehensive understanding of the effectiveness of the monetary incentive program on e-cycling over time. Participants in the program were stimulated to use the e-bike to commute by receiving a fixed monetary compensation for each km they cycled. Because a positive modal shift toward e-cycling was reported, some suggestions for the development of a comprehensive e-bike stimulation program can be made from an equity perspective. One of the conditions within the incentive program was e-bike ownership or the possibility to earn an e-bike by using it. Despite the success of the program, developing similar stimulation programs will not be an effective measure for some groups in society given the relatively high purchase costs of the e-bike. Although e-bike sales have strongly increased over the last couple of years in the Netherlands, some groups in society might still not yet regard the e-bike as potential mode of transport due to, for example, their personal attitude towards (e-)cycling or the subjective norms of people being important to them. Therefore, future e-bike stimulation recruitment strategies can be subdivided into three target user groups. The first group of people are similar to those in the B-Riders who can actively be stimulated to use the e-bike more frequently by offering social incentives and monetary compensation for the actual use of the e-bike. The second potential user group consists of people who are willing to use the e-bike but for whom the purchase of the relative expensive mode of transport compared to the conventional bicycle is a barrier. Using subvention programs to purchase an e-bike decreases this barrier. Although existing studies have shown that e-bike ownership results in e-bike use (Fyhri and Sundfør, 2020; Sun et al., 2020; Kroesen, 2017), this study has shown the increasingly positive effects of stimulating e-bike use over time. In addition, the differences in motivation among people receiving subventions and regular e-bike purchasers remain unclear (see Fyhri and Sundfør, 2020; Sun et al., 2020). Therefore, an incentive program with a combination of stimulating e-bike purchase and e-bike usage might benefit both user groups. For the third group of people without the awareness about the benefits of e-bike use, more general evidence-based e-bike information and experience on e-bike projects might be beneficial for increasing awareness and interest in the potential of this sustainable mode of transport in general. It can also be used to reduce possible negative perceived behavioral control and subjective norms toward e-bike use. Once people's awareness and interest in the e-bike purchase is increased, the strategy for participating in an e-cycling incentive program could be introduced. Since this study does not show a convincing relationship between e-bike use over time and belief-related variables, such as subjective norms, attitudes, and perceived behavioral control, it can be questioned to what extent these variables influence e-bike purchase and e-bike use over time between different user groups.

Encouraging behavioral persistence

This study reports on the increased satisfaction with e-cycling and increase in positive physical health status because of e-cycling over time. This finding is in line with existing understanding that persistence of behavior is important for achieving lasting behavioral changes and creating new habits (Gardner and Rebar, 2019). In practice, short-term e-cycling encouragement programs are developed with the aim of increasing the interest in purchasing and starting to use e-bikes to commute. Within these programs for employers who are often encouraged by governments, employees are provided with e-bikes for some days to first develop the experience of using them. The success rate of these programs is often expressed in people's stated likeliness of purchasing an e-bike. Although studies (Fyhri and Sundfør, 2020; Sun et al., 2020; Kroesen, 2017) have shown that e-bike ownership will substitute for other forms of transport, it remains unclear to what extent e-bikes are used over time for commuting purpose by users in these kinds of programs. In addition to the short-term e-bike introductory programs to stimulate e-bike purchase, this study shows that encouragement toward e-bike use over longer periods of time helps sustain behavioral changes towards e-bike use. Stimulation of e-bike use over longer periods of time based on monetary incentives positively affects people's mental and perceived physical health status. This improved physical health status requires continuation of active travel, which is positively influenced by increased level of satisfaction with travel and establishment of a mutually reinforcing mechanism. However, enabling a modal shift toward more sustainable active behavior and more specifically achieving long lasting behavioral change toward e-cycling requires a more extensive approach than only the development of an e-cycling incentive program. Next, to encourage and sustain the necessary behavioral changes for individuals to continue to cycle to work, the supply of appropriate cycling infrastructure, tax regulations, and subvention regulations for e-bike purchase, charging and parking facilities, travel allowance by tax regulations, and subvention regulations for e-bike purchase by governments and employers are also necessary policies. Based on the specific advantages of extended range and increased comfort the e-bike has to offer compared to the conventional bicycle, the e-bike should be regarded as a specific topic within local and regional mobility policy.

Understanding e-cycling in a broader policy perspective

Over the last decade, collaborating governments are specifically focusing on the increase in cycling shares in the Netherlands to reduce car traffic. In general, policy aims at developing high-quality cycling infrastructure and bicycle parking facilities in addition to stimulation of bicycle usage among different target groups in society, such as children, commuters, and the elderly (Tour de Force, 2022). Often, the degree of success of investment is measured by the outcomes in terms of increased number of cyclists using the cycling infrastructure. However, a recent study has shown (Steenmetz, 2022) that space for improvement in the alignment of cycling policy related investments, measuring outcome in terms of network performance and cycling behavior, and the intended long term sustainability impact exists. Additionally, Dutch cycling policy is often regarded within the scope of transportation policy only and neglects the evaluation of long-term health benefits and environmental impact derived from the switch to cycling. This study shows that the modal shift toward e-cycling leads to a positive increase in people's physical and mental health status over time with an increase in travel satisfaction compared to those undertaking car commuting. As to the intended reduction of car commuting trips, the shift toward the use of e-bikes contributes to people's well-being and therefore social sustainability. With the modal shift brought about by the incentive program combined with the positive effects on both physical and mental health, this study contributes to the discussions evaluating the effectiveness of active mobility measures according to the broad prosperity principles (CPB, 2022, Wee and Mouter, 2021, Bache e.o., 2018). In policy evaluations, as an alternative to existing cost-benefit analyses focusing on modal shift and congestion reduction, changes in well-being, health, urban design, and use of space (less car parking), air quality, which also positively influences health status, and climate mitigation effects should also be considered.

Considering spatial, cultural, and societal context

This study reports on a positive behavioral change brought about by an e-cycling incentive program in the Netherlands. With its specific high-quality cycling infrastructure, rather flat natural environment, temperate maritime climate, and well-developed cycling culture all cycling related circumstances in the Netherlands are likely to contribute to this behavioral change in positive manner. This study does not imply that similar e-cycling stimulation programs would show similar results in other regions and abroad considering variations in the natural and constructed environments and political, cultural, and societal contexts. In many countries around the world cycling is still regarded as a fringe activity. Therefore, future research on the effectiveness of the technical advantages the e-bike offers in a more hilliness environments in terms of increased speed and reduction of pedal effort could show positive modal shift effects compared to conventional cycling. Since this study did not find convincing support for the influences of subjective norm and perceived behavioral control on the shift towards e-bike use over time, future research can be used to elucidate these relationships in less developed cycling cultures.

Concluding thoughts

Finally, this thesis shows the relevance of a longitudinal approach to evaluate the rewarding of modal shift from car use toward active forms of mobility, and specifically the use of the e-bike. The study contributes to a comprehensive understanding of the long-term effectiveness of the monetary incentive program on e-cycling, and how it contributes to the development of sustainable transportation systems. Also, this study provides an example and a framework for studying the effects of incentive programs on the adoption and use of new modes of active transportation, such as e-bikes. The framework is valuable for future research and mobility policies on how to design and evaluate incentive programs to support sustainable transportation behavior over time.

Unique to this study was the full collaboration between cycling policy makers and research in the design of the incentive program and the developed evaluation scheme. Since in practice both disciplines frequently operate along parallel lines, the approach in this study demands a different form and collaboration style between all stakeholders involved. The longitudinal design of the study allows for the scientific evaluation of behavior change over time and the identification of factors that contribute to lasting behavioral change. Additionally, by focusing on the substitutional effect of e-bikes, this study provides insight into how new modes of transportation can be integrated into existing transportation systems and how they can be promoted to achieve sustainability objectives. In addition, this thesis provides valuable understanding about the relevance of monitoring dynamics in travel satisfaction over time related to active travel and specifically e-bike use. Adding these well-being elements to an existing incentive program targeted on congestion reduction, it has enriched and broadened cycling policies over time.

Since recently, this framework to measure travel satisfaction is integrated into the standard approach to measure the behavior and experience of (e-)cyclists in areas in which high-quality regional cycling infrastructure is being developed in the Netherlands. This national approach in measuring cyclists' behavior and experience generates insights in well-being effects brought about by substantial changes in cycling infrastructure. The findings of this thesis can be used to develop targeted policies and programs that encourage the use of alternative active transport options, such as public transportation, biking, and walking. Collaborations between researchers and governments remains important to monitor and evaluate behavioral changes over time via longitudinal studies. This will enable us to design evidence-based policies that will enhance the development of user-oriented sustainable mobility policies.

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Samenvatting in het Nederlands

Achtergrond

Wereldwijd kampen steden en regio's met de uitdaging om de transitie te maken van autogebruik naar meer duurzame vormen van mobiliteit. Beleidsmakers willen met name vervoerwijzen stimuleren die minder schadelijke stoffen uitstoten en daarmee de druk op het milieu verlagen, en steden leefbaarder en gezonder maken. Met name actieve mobiliteitsvormen hebben de voorkeur omdat ze niet alleen een positieve bijdrage hebben aan het milieu, maar ook aan de fysieke en mentale gezondheid van mensen. Hoewel de fiets door beleidsmakers wordt gezien als passend alternatief op de korte en middellange afstanden (<15 km), maken veel mensen de keuze voor een ander vervoermiddel in dagelijks vergplaatsingsgedrag. De aantrekkelijkheid van de fiets als alternatief wordt beperkt door de benodigde fysieke inspanning en de beperkte actieradius. De opkomst van de elektrische fiets biedt nieuwe kansen voor een duurzame gedragsverandering. De afgelopen jaren heeft de e-bike een sterke technologische ontwikkeling doorgemaakt wat betreft het comfort en actieradius, deze betaalbaarder en daardoor beschikbaar is geworden voor een breder doelgroep.

Het afgelopen decennium is het nodige onderzoek gedaan naar de e-bike en de effecten op gedragsverandering. Toch blijft het de vraag in hoeverre e-bike bezit leidt tot meer e-bike gebruik. Uit onderzoek blijkt dat e-bike bezit leidt tot een afname van bezit en gebruik van de gewone fiets, maar dit effect geldt minder voor de auto en het openbaar vervoer gebruik. Alhoewel de kennis over e-bike gebruik toeneemt, bestaat er nog de nodige onzekerheid over de effecten over een langere periode. Daarmee is het niet duidelijk hoe e-bike gebruik van individuen zich ontwikkelt, welke factoren de keuze voor de e-bike beïnvloeden en in welke mate e-bike gebruik effect heeft op het welzijn en de gezondheid van mensen. Dergelijke inzichten zijn belangrijk omdat e-bike gebruik in internationale context een relatief nieuwe vorm van mobiliteit is. De transitie naar e-bike gebruik is daarom een leerproces, waar de dynamiek niet van bekend is. Om tot een transitie van autogebruik naar e-bike te komen is deze kennis wel van belang.

De introductie van e-bikes vindt veelal plaats in stimuleringsprogramma's, waarbij onderscheid kan worden gemaakt in programma's gericht op kennismaking met de e-bike en programma's gericht op het stimuleren van gedragsverandering. In deze laatste groep van programma's worden deelnemers beloond voor e-bike gebruik met monetaire compensatie en niet-monetaire feedback zoals informatie en sociale goedkeuring. Vanuit het oogpunt om ook de e-bike stimuleringsprogramma's te verbeteren, is inzicht in de langere termijn dynamiek in e-bike gedrag en ervaring van het e-biken van belang. Het is daarom van belang om te begrijpen hoe blijvende gedragsverandering kan worden bereikt om daarmee effectief beleid te ontwikkelen om de transitie van autogebruik naar de e-bike niet alleen te maken maar ook te behouden.

Doelstelling en hoofdvraag

Dit proefschrift heeft als doel om inzichten te creëren die bijdragen aan de mobiliteitstransitie naar e-bike gebruik in het dagelijkse woon-werk verkeer op de korte en middellange afstand (<15 tot 20 km). De algemeen bekende nadelen van conventioneel fietsgebruik zoals fysieke inspanning en beperkte range zouden door de technische voordelen van de elektrische fiets (deels) tenietgedaan kunnen worden. Alhoewel er de laatste jaren het nodige onderzoek is gedaan naar de e-bikes, is er slechts in beperkte mate aandacht besteed aan gedragsverandering van forenzen naar e-bike gebruik in het dagelijkse woon-werk verkeer. De centrale vraag in deze thesis is:

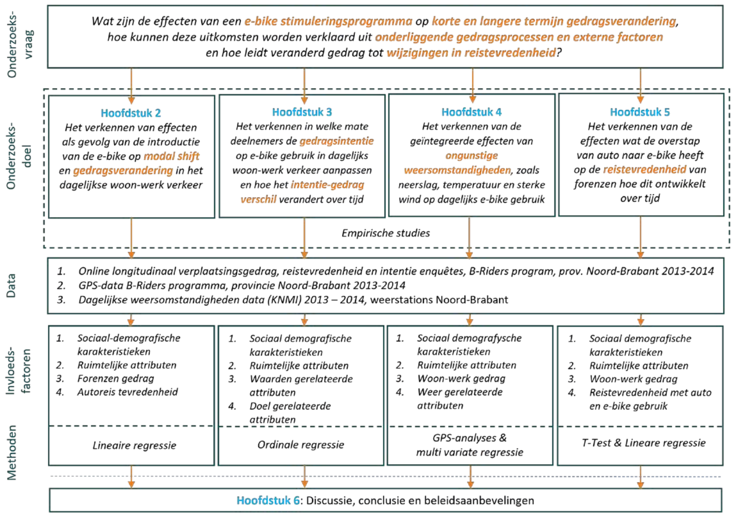
Wat zijn de effecten van een fietsstimuleringsprogramma op korte en langere termijn gedragsveranderingen, hoe kan deze verandering worden verklaard uit de onderliggende gedragsprocessen en externe factoren, en hoe leidt de gedragsverandering tot verandering in reistevredenheid?

Omdat de e-bike wordt gezien als duurzaam alternatief transportmiddel op de korte en middellange afstand begint het proefschrift met een longitudinale verkenning van de modal shift effecten als gevolg van het gebruik van de e-bike in het dagelijkse woon-werk verkeer en in welke mate de gedragsverandering wordt volgehouden door deelnemers. Vervolgens wordt verkend in welke mate deelnemers de intentie om de e-bike te gebruiken aanpassen en het verschil in intentie en gedrag verandert gedurende het e-bike stimuleringsprogramma. Omdat de (elektrisch ondersteunde) fietser is blootgesteld aan wisselde weersomstandigheden wordt vervolgens verkend in welke mate ongunstige weersomstandigheden zoals neerslag, temperatuur en harde wind invloed hebben op het gebruik van de e-bike. Naast het gegeven dat e-bike gebruik een vorm van fysieke inspanning is, en daarmee een vorm van actief transport, is tenslotte onderzocht wat het effect is op de mentale gezondheid en specifiek de reistevredenheid gedurende de deelname aan het stimuleringsprogramma.

Onderzoeksopzet

De basis voor de vier bovengenoemde verschillende deelonderzoeken is een grootschalig e-bike stimuleringsprogramma (B-Riders) in de Nederlandse provincie Noord-Brabant. Met een ruimtelijke ordening waarbij 86% van de bevolking op een afstand tot 15 kilometer van de vijf grootste steden woont en voorzien is van hoogwaardige fietsinfrastructuur, biedt deze regio een goede context om de mogelijke gedragsverandering naar meer gebruik van de e-bike in het dagelijkse woon-werk verkeer te onderzoeken. Als voorwaarden voor deelname aan het programma geldt dat deelnemers zich de helft of meer dagen van de week met de auto van huis naar het werk verplaatsten, een minimale woon-werk afstand hebben van drie kilometer, tussen de 18 en 65 jaar oud zijn en werkzaam zijn in Noord-Brabant. Ook moesten deelnemers het aanschafbewijs van een e-bike overhandigen om zeker te zijn dat ze geen bestaande e-bike gebruikers waren. Omdat het programma primair gericht was op het reduceren van autogebruik in de spitsperioden kregen deelnemers een monetaire stimulans van €0,15 per gefietste kilometer in de spits en €0,08 per gefietste kilometer in de daluren met een maximum totaalbedrag van €1.000,- (duizend euro). Om deelnemers te werven, is gebruik gemaakt van kranten en sociale media.

Voor het onderzoek zijn twee verschillende onderzoeksmethoden ingezet. De eerste methode is een reeks van online vragenlijsten die deelnemers aan het stimuleringsprogramma verplicht moesten invullen. De tweede methode is gericht op het registeren van het daadwerkelijke verplaatsingsgedrag door middel van GPS-locatie bepaling op de mobiele telefoon. Aanvullend is gebruik gemaakt van KMNI-data met betrekking tot dagelijkse weersomstandigheden gedurende het programma. Deelnemers aan het programma is gevraagd op een drietal momenten een online vragenlijst in te vullen, waarbij gevraagd werd naar het huidige en verwachte toekomstige verplaatsingsgedrag, de ervaring met de auto- en e-bike rit en de omgeving, het verwachte gedrag bij variërende weersomstandigheden en de persoons- en huishoudenskenmerken. De eerste vragenlijst is afgenomen bij de start van deelname aan het programma en is gericht op de ervaring met het huidige autogerichte woon-werk verplaatsingsgedrag en het verwachte e-bike gebruik. Met de tweede vragenlijst wordt gedragsverandering en de ervaring met de e-bike in de eerste maand uitgevraagd en de mogelijk aangepaste verwachting van het e-bike gebruik in de voorliggende periode. De derde vragenlijst is gericht op de gedragsverandering na een half jaar deelname en de opgedane ervaring met de e-bike rit naar het werk. In een parallel spoor is gedurende het programma het verplaatsingsgedrag van de deelnemers continue gemeten door middel van GPS-locatiebepaling via de mobiele telefoon. Deze data werden vanuit het stimuleringsprogramma ook gebruik voor het bepalen van de financiële vergoeding op basis van het daadwerkelijke en gewenste e-bike gebruik. De onderstaande figuur geeft een overzicht van de onderzoeksopzet.



Resultaten

Hoofdstuk 2 geeft inzicht in de gedragsverandering die teweeg is gebracht door de introductie van de e-bike en in hoeverre dit gedrag volgehouden is. Met een modal shift waarbij een maand na de start twee derde van alle woon-werk ritten met de e-bike worden afgelegd lijkt het stimuleringsprogramma een substantiële impact te hebben op de gedragsverandering. Als gekeken wordt naar de initiële vervoerwijzenkeuzen voorafgaand aan de deelname aan het programma dan blijkt dat naast woon-werk autoritten ook woon-werk ritten met de conventionele fiets vervangen worden door ritten met de e-bike. Deze uitkomst is in lijn met eerder onderzoek waarbij blijkt dat e-bike bezit het gebruik van de conventionele fiets substitueert. Dit geldt met name op de kortere ritten tot 10 kilometer, waar boven de 10 kilometer de nadruk ligt op de substitutie van autoritten. Het substitutie effect naar meer e-bike gebruik neemt op de langere termijn toe, waarbij ook een toename van de fysieke gezondheid wordt gerapporteerd. Omdat uit lineaire regressie blijkt dat het gebruik van de conventionele fiets voor woon-werkverkeer van invloed is op het potentieel gebruik van de e-bike is in de analyses een onderscheid gemaakt tussen forenzen met en zonder fietsroutine. Met name de groep die voorafgaand aan het programma alleen de auto gebruikte laat de grootste gedragsverandering zien. Ook geslacht, autobezit en huishoudenssamenstelling zijn van invloed op de modal shift, waar deze studie geen duidelijke relatie laat zien met de stedelijkheidsgraad van de huislocatie.

In hoofdstuk 3 wordt inzicht gegeven in de verandering in gedragsintentie en de mate van intentie- en gedragsconsistentie gedurende het programma. Uit onderzoek blijkt dat twee derde van alle deelnemers zijn of haar gedragsintentie niet aanpast. Er kan gesteld worden dat de groep autogebruikers iets minder consistent is ten opzichte van de groep die twee of meer dagen met de conventionele fiets naar het werk ging. De autogebruikers gebruiken de e-bike meer dan in eerste instantie de intentie was. Van alle deelnemers die hun intentie aanpasten stelde twee vijfde de intentie bij naar minder en drie vijfde naar meer e-bike gebruik. Met name de groep met veel conventionele fietservaring laat met 83% een consistente gedragsintentie zien. Door de longitudinale onderzoeksopzet is het mogelijk de intentie-gedragsconsistentie te analyseren. In de eerste maand van deelname aan het programma laten iets meer dan 50% van de deelnemers hetzelfde gedrag zien dan ze vooraf als intentie hadden aangegeven. Daarnaast maakt 41% van de deelnemers minder gebruik van de e-bike en 8% van de deelnemers meer ten opzichte dan de initiële intentie. De groep deelnemers met (conventionele) fietservaring is hierbij consistenter dan de autogebruikers. In de vervolgperiode blijft de groep met dezelfde intentie als gedrag nagenoeg gelijk, waarbij de groep deelnemers die onder-presteert vermindert en de groep die over-presteert toeneemt. In aanvulling op deze resultaten laat deze studie geen duidelijke relatie zien tussen persoonlijke waarden gerelateerde variabelen (belief-related variables) als attitude, sociale norm en waargenomen gedragscontrole (perceived behavioral control), doel gerelateerde variabelen (goal-related variables) als verwachte emoties, de wens en haalbaarheid van het doel, en de consistentie tussen intentie en gedrag. Dit kan wellicht verklaard worden door het gegeven dat de aanschaf van een e-bike randvoorwaardelijk was voor deelname aan het e-bike stimuleringsprogramma, waardoor aangenomen kan worden dat deelnemers al een positieve mindset en intentie hadden ten aanzien van e-bike gebruik.

Hoofdstuk 4 geeft inzicht in de invloed van ongunstige weersomstandigheden als neerslag, temperatuur en harde wind op het e-bike gebruik in het dagelijkse woon-werk verkeer. Waar uit eerder onderzoek al is gebleken dat deze ongunstige weersomstandigheden een negatief effect hebben op conventioneel fietsgebruik, laat deze studie het effect op e-bike gebruik zien. De effecten zijn in beeld gebracht door een combinatie van longitudinale GPS-data, gemeten weersomstandigheden van regionale weerstations en sociaal-demografische informatie van deelnemers. Deze studie laat zien dat luchttemperatuur, windsnelheid en neerslag de kans op e-bike gebruik aanzienlijk beïnvloeden. Het is opmerkelijk dat de toevoeging van gedragsintentie gerelateerd aan temperatuur en neerslag een significant positieve invloed hebben op e-bike gebruik, maar dit voor het toevoegen van gedragsintentie bij winderige omstandigheden niet het geval is. Mogelijk is de beleving wind minder van invloed op het e-bike gebruik door technische voordelen van de e-bike, waardoor de fietser minder inspanning hoeft te leveren om de fietsrit te maken. Wordt gekeken naar de e-bike als alternatief voor woon-werk autogebruik, dan blijkt dat deelnemers met een tweede auto in het huishouden frequenter de auto lijken te gebruiken bij slechter weer. De groep deelnemers uit meerpersoonshuishoudens met slechts één beschikbare auto is waarschijnlijker de e-bike te gebruiken bij regen en relatief koude weersomstandigheden. Ondanks de technische voordelen van de elektrische fiets waarmee de fysieke inspanning verlaagd wordt wat leidt tot een toename van e-bike gebruik, lijken de ongunstige weersomstandigheden de keuze om de autorit door e-bike gebruik te vervangen te beperken.

Hoofdstuk 5 beschrijft in welke mate de gedragsverandering van auto naar e-bike gebruik tijdens woon-werkritten invloed heeft op de reistevredenheid van mensen en hoe deze ontwikkelt. Over het algemeen is het effect van stimuleringsprogramma's beperkt, aangezien veel mensen weer terugvallen in oude gewoontes. Aangezien e-bike gebruik een vorm van actief transport is, beïnvloedt het zowel de fysieke als de mentale gezondheid positief en leidt het tot een toename in aantrekkelijkheid van fietsen. Bij de start van het programma is deelnemers gevraagd naar de reistevredenheid van de autorit en de verwachte reistevredenheid met de e-bikerit. Een maand na de start is de deelnemers gevraagd naar de ervaren reistevredenheid met de e-bike naar het werk, waar na zes maanden deze meting nogmaals herhaald is. Door de longitudinale opzet van deze studie is het mogelijk de reistevredenheid met de autorit, de verwachte verandering en de tevredenheid van de e-bikerit over een langere periode te meten om daarmee de aantrekkelijkheid of het plezier van e-bike gebruik weer te geven. Deze studie laat zien dat deelnemers met een positieve tevredenheid over de autorit aan het programma startten, waar zowel deelnemers met en zonder fietservaring nagenoeg dezelfde positieve verwachting hadden van de tevredenheid met het e-bike gebruik. Alhoewel de gemiddelde daadwerkelijke tevredenheid met het e-bike gebruik (1,85 op een schaal van -3 tot 3) na een maand iets lager lag dan de deelnemers vooraf verwachtten (2,02), was deze significant hoger dan de reistevredenheid met de auto (0,56). Ook na een half jaar liet deze studie vergelijkbare effecten (1,95) zien ten aanzien van tevredenheid wat impliceert dat er geen afzwakking- of gewenningseffecten optreden. Het gebruik van lineaire regressiemodellen laten geen significante relatie zien met persoons- of huishoudenskenmerken. Wel ervaren forenzen uit huishoudens met één auto een grotere toename in de reistevredenheid ten opzichte van forenzen met twee of meer beschikbare auto's. Ook heeft de ruimtelijke context invloed op de tevredenheid, waar deelnemers uit sterk en matig stedelijke omgeving een lagere tevredenheid hebben dan degene uit rurale niet stedelijke gebieden. Verder laat deze studie zien dat de mate van groen en levendigheid van de omgeving een positieve invloed heeft op de beleving. Alhoewel de ervaren fysieke gezondheid geen direct effect heeft op de reistevredenheid, heeft de toegenomen gezondheid door e-bike gebruik een positief effect op de reistevredenheid.

Wetenschappelijke bijdrage

Dit proefschrift levert op vier aspecten een bijdrage aan de bestaande wetenschappelijke kennis. Allereerst levert dit onderzoek een basis om de longitudinale impact op gedragsverandering als gevolg van een e-bike stimuleringsprogramma voor verschillende gebruikersgroepen te begrijpen. In algemene zin kan gesteld worden dat het stimuleringsprogramma succesvol was in de blijvende substitutie van auto naar e-bike gebruik gedurende het programma. In aanvulling daarop is een onderscheid gevonden in zowel woon-werk afstand als (conventionele) fietservaring. Op woon-werk afstanden tot 7.5 kilometer werd met name de conventionele fietsrit vervangen door de e-bike, waar in de afstanden tussen 7.5 en 20 kilometer de daadwerkelijke substitutie van auto naar e-bike gebruik plaats heeft gevonden. In lijn met andere studies toont dit onderzoek aan dat bestaande (conventionele) fietservaring invloed heeft op de gedragsverandering. In het algemeen laat deze studie zien dat het stimuleren van fietsgebruik een effectieve interventie is voor gedragsverandering naar meer e-bike gebruik. Daarnaast toont de studie aan dat het stimuleren van gebruik in plaats van het stimuleren van bezit een effectief instrument is voor gedragsverandering. Deze studie impliceert ook dat zowel de uiteindelijke vervoerswijzekeuze als de modal shift belangrijk zijn in de effectevaluatie van een dergelijk stimuleringsprogramma. Het waargenomen e-bike gebruik is het gevolg van een mobiliteitstransitie, waarbij naast de beoogde mobiliteitstransitie van autogebruik naar e-bike gebruik ook onvoorziene substitutie effecten van conventioneel fietsgebruik zijn opgetreden.

Ten tweede geeft dit onderzoek belangrijk inzicht in de relatie tussen gedragsverandering en de tevredenheid over de verplaatsing. Naast het gegeven dat stimuleren van e-bike gebruik effect heeft op langdurige gedragsverandering, laat deze studie een toenemende tevredenheid met het e-bike gebruik zien. Ook laat deze studie een toename zien in de gerapporteerde fysieke gezondheid. Dit suggereert dat verplaatsingsgedrag, reistevredenheid en gezondheid aan elkaar gerelateerd zijn en elkaar kunnen versterken. Waar de verandering naar meer e-bike gebruik een toename in reistevredenheid tot gevolg had, is het denkbaar dat een toename in reistevredenheid ook tot een toename in waarschijnlijkheid leidt dat deelnemers ook blijven e-biken. Ook is het positieve gezondheidseffect als gevolg van fietsen (wat ook geldt voor e-bike gebruik) uit eerdere studies bekend. Eerder studies hebben aangetoond dat de gezondheid invloed heeft op de waarschijnlijkheid van fietsgebruik, maar dat ook de ervaring met actief transport afhankelijk is van de fysieke gezondheid. Deze samenhang suggereert dat een toename in fysieke gezondheid door fietsgebruik, leidt tot een toename in waarschijnlijkheid dat dit gedrag in stand wordt gehouden. Het resultaat van deze studie impliceert dat bij het ontwikkelen van nieuwe interventies om actief transport te stimuleren rekening gehouden moeten worden met deze drie aspecten (verplaatsingsgedrag, reistevredenheid en gezondheid).

Een derde bijdrage van dit proefschrift heeft betrekking op de invloed van waarden-gerelateerde variabelen (belief-related variables), doel-gerelateerde variabelen (goal-related variables) en gewoontegedrag (habit) op gedragsintentie en de daadwerkelijke gedragsverandering naar e-bike gebruik. In deze studie is geen significant verband aangetoond tussen de waarden- en doel-gerelateerde variabelen uit onder meer de Theory of Planed Behavior, zoals attitude, sociale norm en gedrag. Dit zou wel verwacht mogen worden vanuit bestaande literatuur over gedragsintentie en daadwerkelijk gedrag. Wel bestaat er een verband tussen gewoontegedrag en gedragsverandering. Er kan verondersteld worden dat, door de noodzakelijke aankoopinvestering, vooral gemotiveerde deelnemers, met een positieve houding ten aanzien van e-bike gebruik, aangetrokken zijn. Een ander aspect wat van invloed zou kunnen zijn geweest om de uitkomst van deze studie is de sociale norm of mening van mensen uit de sociale omgeving die belangrijk zijn voor de deelnemer(s). Deze studie laat zien dat naast de sociale norm, ook de stimuleringsstrategie gericht op het beïnvloeden van de persoonlijke attitude en de ervaren haalbaarheid van het doel geen invloed hebben op de gedragsintentie en het gedrag van deelnemers. Dit betekent niet dat deze factoren geen invloed hebben, maar wellicht spelen deze factoren in een eerder stadium van e-bike gebruik, zoals voor forenzen die zich aan het oriënteren zijn op e-bike gebruik, welke in deze studie niet meegenomen zijn.

Beleidsimplicaties

Op het moment van schrijven is in Nederland het Nationale Tour de Force programma ontwikkeld, waarbij samenwerkende overheden de gezamenlijke ambitie hebben geformuleerd om tot een schaalsprong in het fietsgebruik te komen. Ondanks alle voordelen die de fiets biedt in termen van bereikbaarheid, fysieke en mentale gezondheid en impact op het milieu maakt een aanzienlijk deel van de mensen er nog geen gebruik van in het dagelijkse verplaatsingsgedrag. Naast de aanleg van hoogwaardige fietsinfrastructuur en het realiseren van fietsparkeervoorzieningen wordt nadrukkelijk ingezet op fietsstimulering. Dit maakt inzichten in het stimuleren van de elektrische fiets met haar technische voordelen waar het gaat om lagere fysieke inspanning en hogere actieradius, erg relevant. De resultaten van deze studie laten zien dat er vijf beleidsimplicaties zijn voor duurzame gedragsverandering. Vanuit beleidsmatig perspectief wordt het B-Riders fietsstimuleringsproject als succesvol gezien vanwege het aantal mensen dat heeft deelgenomen. Naast de verschillende elektrische fiets stimuleringsinitiatieven die de afgelopen jaren ondernomen zijn, vaak gericht op het stimuleren van e-bike aankoop, biedt deze studie specifiek inzicht in het stimuleren van e-bike gebruik over een langere periode. Om de effectiviteit van een dergelijk stimuleringsprogramma verder te verhogen kan de opzet specifieker gericht worden op de middellange woon-werk reisafstanden, door het toevoegen van variatie in de financiële vergoeding en sociale feedback ontstaan mogelijk kansen op effectievere gedragsverandering, en het aanpassen van werkgeversregelingen kan de aanschaf van e-bikes voor woon-werk verkeer aanmoedigen. Uit deze studie blijkt dat de e-bike op de korte afstanden met name de conventionele fietsverplaatsing vervangt. Met het oog op de beoogde duurzaamheidseffecten als het reduceren van de congestie, het verlagen van de negatieve impact op het milieu en het verhogen van de leefbaarheid en gezondheid, heeft dit mechanisme een beperkte toegevoegde waarde. Dit impliceert dat de opzet van een e-bike stimuleringsprogramma nog nadrukkelijker gericht moet zijn op de vervanging van woon-werkautoritten op de middellange afstanden tot 20 kilometer. Daarnaast is in het huidige stimuleringsprogramma de financiële compensatie voor het gewenste gedrag vastgesteld, waar het de vraag is in hoeverre variaties in de hoogte van de compensatie gedurende de looptijd van het project van invloed zouden zijn op de resultaten. Ten derde is het interessant om naast de financiële beloning ook alternatieve feedback toe te voegen. Deze feedback kan gegeven worden op persoonlijk/individueel niveau ten aanzien van de geleverde prestatie en op collectief niveau, waarbij de werkgever actief bijdraagt aan een positieve fietscultuur. Ook is het actief betrekken van de werkgever van toegevoegde waarde, waar deze werknemers die op e-fietsafstand wonen actief kan benaderen en haar werkgeversregeling kan aanpassen. Tenslotte kunnen beleidsmakers de werkgevers actief ondersteunen om aanpassingen binnen de werkgeversregelingen mogelijk te maken om bijvoorbeeld de relatief dure e-bike aan te kunnen schaffen.

Deze studie biedt inzicht in de effecten van het stimuleren van e-bike gebruik in het dagelijkse woon-werk verkeer. Wordt er echter vanuit een gelijkheidsperspectief gekeken dan biedt het huidige programma niet voor alle groepen uit de samenleving uitkomst. Ondanks de sterke groei in e-bike verkopen de afgelopen jaren, beschouwt niet iedereen de e-bike als een passend alternatief vanuit eigen waarden en normen of als gevolg van sociale druk vanuit mensen in de naaste omgeving. Bij de ontwikkeling van e-bike stimuleringsprogramma's kan onderscheid gemaakt worden naar drie verschillende doelgroepen. De eerste groep zijn mensen die gestimuleerd kunnen worden door middel van financiële en sociale feedback, vergelijkbaar met de huidige deelnemers. De tweede groep bestaat uit mensen die positief tegenover het gebruik van de e-bike staan, maar voor wie de relatief dure aanschafprijs een barrière vormt. Daarom zou een stimuleringsprogramma wat inzet op zowel het vergemakkelijken van de aanschaf als het stimuleren van e-bike gebruik mogelijk uitkomst bieden voor deze twee doelgroepen. Een derde groep aan mensen die nog minder bekend zijn met de mogelijkheden van een e-bike, zou mogelijk geholpen zijn met op bewijs gebaseerde informatie over de potentiële voordelen van e-bike gebruik binnen de persoonlijke omstandigheden. Voor deze groep biedt actieve kennismaking met het gebruik van een e-bike, door bijvoorbeeld e-bike probeeracties bij de werkgever, mogelijk uitkomst.

Een belangrijke uitkomst van het onderzoek is de relatie tussen de toegenomen tevredenheid met het e-bike gebruik in combinatie met de toename van fysieke gezondheid door het e-bike gebruik gedurende het programma. Waar in de praktijk de nodige stimuleringsprogramma's gericht zijn op de aankoop van of eerste kennismaking met de elektrische fiets, laat deze studie zien dat het stimuleren van het elektrische fietsgebruik bijdraagt aan het volhouden van gedragsverandering. E-bike gebruik als vorm van actief transport draagt positief bij aan de fysieke en mentale gezondheid, wat op haar beurt weer positief bijdraagt aan de tevredenheid met de verplaatsing wat een wederzijds versterkend mechanisme teweegbrengt. Naast het stimuleren en onderhouden van gedragsverandering dienen ook de aanwezigheid van passende fietsinfrastructuur, fietsparkeer- en oplaadvoorzieningen, wet- en regelgeving en subsidieregelingen beschikbaar te zijn gesteld door de overheid en werkgevers. Door de specifieke voordelen van de elektrische fiets als het gaat om een grotere actieradius en toename in comfort ten opzichte van de conventionele fiets, zou de e-bike als afzonderlijk vervoermiddel behandeld moeten worden in het lokale en regionale mobiliteitsbeleid.

De afgelopen jaren hebben de samenwerkende overheden zich met name gericht op het verhogen van het fietsgebruik met als doel om met name het autogebruik te verminderen. Investeringen in hoogwaardige fietsinfrastructuur, fietsparkeervoorzieningen en het stimuleren van fietsgebruik zijn vooral gericht op groei in aantal fietsers op het fietspad. De mate van het succes van fietsbeleid wordt veelal binnen de context van mobiliteitsbeleid afgewogen, waarmee positieve lange(re) termijn gezondheidsbaten en impact op het milieu achterwege worden gelaten. Deze studie laat zien dat naast de beoogde gedragsverandering ook de mentale gezondheid en het welzijn van mensen verbetert. Daarmee kunnen deze effecten gerelateerd worden aan de huidige maatschappelijke dialoog over brede welvaart en sociale duurzaamheid.

Uiteraard kunnen de positieve resultaten van deze studie niet los worden gezien van de Nederlandse context, waarbij de hoogwaardige fietsinfrastructuur, het relatief vlakke landschap, het gematigd zeeklimaat en de Nederlandse fietscultuur positief bijdragen aan de gunstige omstandigheden voor deze studie. Ondanks de technische voordelen van een e-bike is het de vraag in hoeverre vergelijkbare resultaten behaald kunnen worden in een andere natuurlijke, politieke, culturele en maatschappelijke context. Het blijft daarmee de vraag of de technische voordelen van de elektrische fiets zich ook door vertalen naar meer bergachtige omgeving. Alhoewel in de Nederlandse context de invloed van sociale normen op e-bike gebruik en ervaren voertuigbeheersing van de e-bike geen rol lijken te spelen, blijft het de vraag of dit ook geldt in landen met een minder ontwikkelde fietscultuur.

About the Author

Joost de Kruijf was born in august 1976 in ’s-Hertogenbosch, the Netherlands. He received his bachelor’s degree in Transportation Engineering in 1999 from the Breda University of Applied Sciences. After that, he started his master‘s degree in Urban Geography at the Utrecht University and graduated in 2002. In a parallel vein, Joost started his career as a traffic forecast modeling specialist in 1999 supporting government in anticipating on impact of future mobility.

In 2011, Joost moved to the Breda University of Applied Sciences to focused more on research and innovation in the field of transportation and the built environment. At that time, he started his PhD research at the department of Human Geography and Spatial Planning at the Utrecht University.

Most of his research concentrates on data-driven (cycling) policy and business enhancement including topics as accessibility, user-experience, network planning and digital twinning. In his current work, Joost focusses on establishing strong connections between science, government, and industry in the field of mobility, built environment and data solutions.

His works are published in a variety of peer-reviewed international journals, including Transportation Research part A, Travel Behaviour and Society, Journal of Transport and Health, Transportation Research Procedia, Landscape and Urban Planning, Journal of Transport Geography, and Computers, Environment and Urban Systems.

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E-cycling to work

This research focuses on the effects of an e-cycling incentive program on short- and longer-term behavioral changes, and how the outcomes can be explained based on underlying behavioral processes and external factors. The investigation also looked into the change in behavior and how this resulted in changes in travel satisfaction. By applying a longitudinal approach, a group of participants in an e-bike incentive program was followed, using a series of online questionnaires and GPS-data.

In total, two-thirds of the original commuting trips were replaced by e-bike trips. The research reveals two substitution effects. For distances up to 10 kilometers, conventional bicycle trips are substituted by the use of the e-bike and for distances above 10 kilometers, e-bikes replace car trips. This research also shows that two-thirds of all participants are consistent when comparing their behavioral intention and actual behavior. During the program, the other participants adjust their behavior, with this group making more use of the e-bike. The research results also show that the likelihood of e-bike use is influenced by air temperature, wind speed and precipitation. Despite the technical advantages of the electric bicycle, which reduces the required physical effort which leads to an increase in the use of e-bikes, the adverse weather conditions seem to make the choice to permanently abandon the car too difficult.

This research shows that there is a positive relationship between the increase in physical health and travel satisfaction, which increases the attractiveness of e-bike use and positively influences behavioral change. This study contributes to both scientific knowledge in the field of longitudinal behavior change as well as practical implications when it comes to developing behavioral change incentive programs.