IMPLICATIONS OF INCREASED E-BIKE USAGE

An analysis of the modal shift to e-bikes in the Netherlands

M.L.F. Swaalf

Implications of increased e-bike usage

by

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Cover: Cyclist on e-bike (source,2019)

TU Delft

Abstract

This research has attempted to provide insights on the increasing usage of e-bikes and the factors contributing to this phenomenon in Dutch context. This was done in two parts, a literature study and a data analysis. The literature study led to the hypotheses that the factors car ownership, trip length, urbanization and trip purpose were significant gaps to be investigated for modal shift.

The data analysis was done by analysing modal shift of the longitudinal data set from the Netherlands Mobility Panel survey. The e-bikers' modal shift patterns before and after acquiring an e-bike are investigated. The findings indicate that after e-bike adoptions, conventional bike is significantly reduced. For the other modes of transportation, the results are inconclusive. The other factors, car ownership, trip length, urbanization and trip purpose have limited to no effect on modal shift. Across these factors, only for the trip purpose of shopping does e-bike adoption have a significant reduction in car use.

Contents

1 Introduction

1.1 Problem Description

The increased usage of e-bikes has been an interesting phenomenon throughout the 21st century. Electronic bikes (e-bikes) differ from a traditional bike, as they are driven with the help of a battery, coupled to an electric motor. Because of characteristics including low cost, speed, convenience, and long trip distance of e-bikes, significant increase has been noticed Gao et al. [2021]. Moreover, the increasing population, the increase in jobs in a city radius, and the shifting popularity compared to traditional bikes have made e-bikes even more popular. The market size for e-bikes in the US, for example, is expected to more than double from 2021 to 2027 Statista Research Department [2023]. The increase is particularly interesting, as even though the concept of the electric bike is 120 years old Bolton Jr. [1895], the emergence has been relatively recent.

Throughout other countries, similar trends are emerging. Additionally, hopes are high that e-bikes can play a role in decarbonizing road transport, reducing air and noise pollution, and easing traffic congestion Mandake and Bankar [2020]. However, modal shift behaviour analysis needs to conclude for which modes of transportation substitutions to e-bikes are being made. In the case for car substitutions, the positive effects may be considerable, as the emission rate per passenger kilometre of an e-bike is significantly lower than that of a car Sun et al. [2020]. For other modes of transportation, these effects may be more limited. Therefore, more insight on the topic of modal shift behaviour is required.

Also, disparities between countries play a massive role on the implications of local e-bike usage. For example, the substitution of cars by e-bikes in Austria is mainly done for leisure purposes and rarely for commuting Wolf and Seebauer [2014]. In the Netherlands, a different preference for mode usage may be present Sun et al. [2020]. This study will be focussing specifically on Netherlands.

Different definitions occur throughout the literature, as Asian and Western interpretations differ. In Asia, an e-bike is usually and electric scooter or pedelec, accelerating with a gas pedal. In Europe and the United States, e-bikes generally refer to bikes with electric pedal assistance. In this research, the latter definition is applied.

1.2 Research questions

Because of all the factors mentioned above, an increase in e-bike usage is hypothesised. Partly due to a general increase in traffic usage, but also due to the modal shift behaviour. The objective of this research is to quantify the e-bike usage increase from the modal shift behaviour. This has led to the following research question with three sub-questions. The

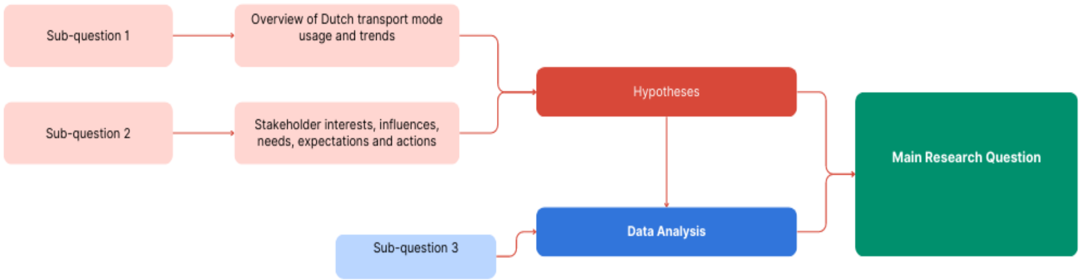


Figure 1.1: Research questions

main research question is: What are the main factors that have caused the increase in e-bike usage in the Netherlands from 2017 to 2020?

1. What is the total usage and of e-bikes, traditional bikes, cars, and public transport in the Netherlands in the years 2017 to 2020?
2. What stakeholders are involved for enabling the increase to e-bikes?
3. To what extent are e-bikes replacing traditional bikes, cars, and public transportation?

The first sub-question will be answered through statistical data, found on the Dutch Institute for Transport Policy Analysis. An overview of the overall usage of all transport modes, including motivations and opinions on each travel mode, gives a good initial understanding of the research topic. The second sub-question involves a stakeholder analysis. The most important stakeholder in this research are the commuters, both e-bike and non-e-bike users. Other potential stakeholders, like the government and the e-bike manufacturer, are also investigated. A literature review will be the best way for completing this analysis. For the third sub-question, the existing literature on modal shift to e-bikes is reviewed. Then, a hypothesis is made, after which a model is chosen to analyse the data from the Dutch Mobility Panel (MPN).

1.3 Report Structure

First, the methodology for the data analysis will be discussed in chapter 2. Then, a literature study on the status quo is conducted in chapter 3, as is the stakeholder analysis. After that, the results of the data analysis are conducted in chapter 4. Finally, the conclusions and recommendations are discussed in chapter 5 and 6 respectively.

2 Literature review

In this chapter, the literature is reviewed to answer the first two sub-questions. First, the past research is discussed to check for expected results and methodology. Next, the transport modes in the Netherlands are analysed in order to get a clear understanding of Dutch transport behaviour. Additionally, the investigated factors for the hypotheses are discussed. Next, the stakeholders are discussed.

2.1 Past research

A lot of research on several relevant sub-topics has already been conducted. To check for research gaps, modal shift in other countries and other travel modes will be analysed. Local results are widely varied, as researched by the following studies from other countries. In terms of trip purpose, some studies conclude e-bike use is only for commuting MacArthur et al. [2014], others conclude it's mostly for leisure Wolf and Seebauer [2014] or mixed Fyhri and Fearnley [2015]. Therefore, only general conclusions from research abroad must be considered.

As e-bike usage started in China, the earliest research was done there. In a survey research, Cherry and Cervero [2007] found that e-bikes, during this period, mostly replaced traditional bikes and bus trips. A later study by Cherry et al. [2016] found after prolonged e-bike exposure, car trips are also replaced by e-bikes. Main factors for e-bike adaption are income level and age, with higher income and higher age being more likely to reduce their car usage.

In the Netherlands, two studies are most relevant for this research. A study performed by Kroesen [2017] examined modal shift through a national survey, with approximately 40,000 respondents. It concluded that e-bike ownership strongly reduces traditional bike use, but also car and public transport use. The reductions in mean distance travelled are 66% for traditional bikes, 28% for cars as a driver and 64% for public transport. Car travel as a passenger saw a slight increase of 5%. Another conclusion is that car ownership does not negatively affect e-bike use as strongly as traditional bike or public transport use.

Another study, performed by Sun et al. [2020] confirms these conclusions to a lesser extent. After adopting to an e-bike, traditional bike use drops 90%, and car use as a driver drops 20%. Similarly, car use as a passenger remains unaffected. Though public transport is categorized slightly differently in the study, usage drops approximately 25%. Other conclusions include that less urbanized areas are more likely to reduce their car use, albeit partly due to their already higher car usage. The factor of trip distance is also studied, as e-bikes mostly replace trips for distances between 5 and 15 km. Trip purpose was also investigated, with conclusions that e-bikes significantly replaces cars for shopping and commuting purposes, but not for leisure or transportation. It should be mentioned for both studies that car use remains the primary mode of transportation.

This research wants to contribute to the existing literature through its unique data collection. Most studies perform a survey, which generally includes a questionnaire and a travel diary. The travel diary requires participants to remember trip length, duration, or other data from memory, which has its limitations. The data used in this study forgoes this problem, as GPS data is included. Additionally, this research aims to follow up on the research already conducted by the MPN. The data for 2013 to 2016 has been analysed by Sun et al. [2020], and the 2017 and 2018 data has been analysed by de Haas et al. [2022], albeit with a different approach. Another research gap that will be investigated in this study, is the effect e-bike ownership has on car ownership, as Sun et al. [2020] found this to be inconclusive. Another research gap that was found among these studies, is that they generally only investigate shares of passenger kilometers, rather than the shares of the total number of trips. This is generally the case due to survey limitations, as is the case in Kroesen [2017]. Therefore, this study will include both.

2.2 Transport in the Netherlands

The Netherlands is known for its large share of bicycle use Martens [2013]. It is the unrivalled number one nation in bicycle use with 26% of trips being made by bicycle Ministry of Infrastructure and Water Management and Rijkswaterstaat [2018], with Denmark (18%) and Germany (10%) in second and third respectively. As the impact of e-bikes is investigated, the impact on factors such as trip length, age, education level and income are researched to form the hypotheses.

Shorter trips (¡15km) make up the majority of cycling trips Sun et al. [2020], and are therefore most likely to be impacted by e-bike adoption. This is intuitive, as most trips are made to remain within a certain time limit. Longer cycling trips, however, are most likely made for recreational purposes McQueen et al. [2020] such as race cycling, so e-bikes are unlikely to have an impact.

Even though an e-bike is relatively expensive compared to a traditional bike, they tend to be more adopted by lower income and lower educated households. This has multiple reasons; higher income households generally keep their car, forgoing the use of an e-bike. Additionally, the distance to work for lower income households is generally shorter, making e-bikes a better alternative An et al. [2013] Simsekoglu and Klöckner [2019b].

Age and gender have a limited impact on e-bike use, as the perceived benefits from e-bike use go up with age Simsekoglu and Klöckner [2019a]. However, most studies don't find conclusive results Ling et al. [2017] An et al. [2013]. Some studies do find a relationship between older age groups and an increase in e-bike use Haustein and Møller [2016], where the reasons are concluded to be the additional spare time for recreational trips, lower tendency for car use, and the physical benefits. As for gender, it varies per group of participants whether women have a bigger increase compared to men. Due to the limited effect, these factors will not be taken into account.

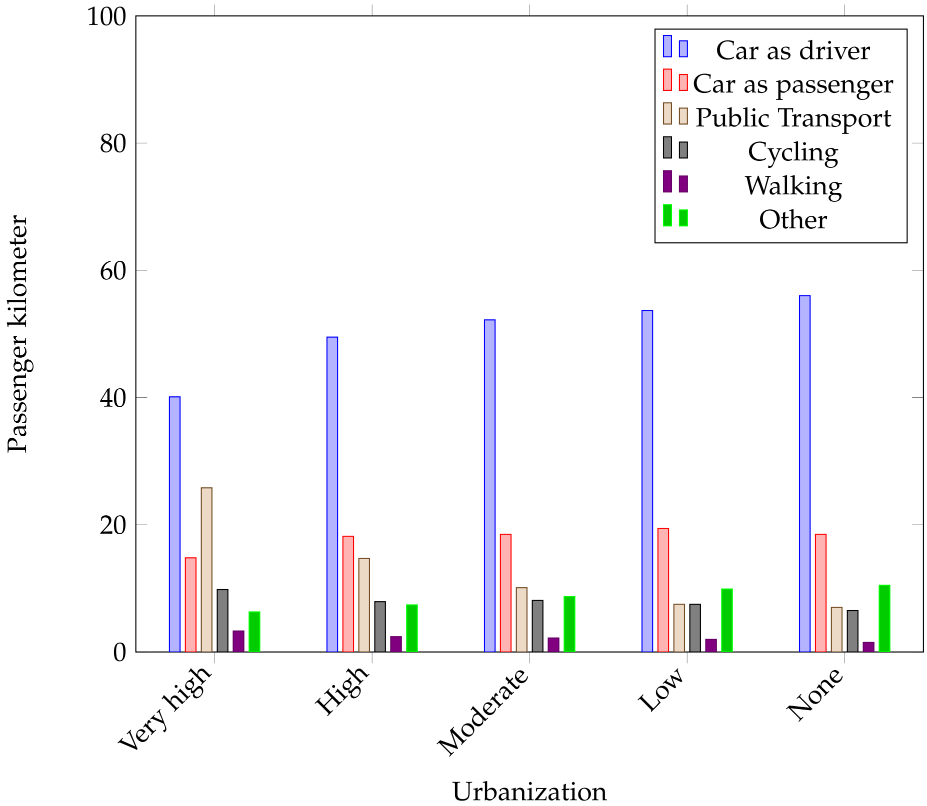


Figure 2.1: Transport mode shares compared to urbanization in the Netherlands in 2019 CBS [2022]

In this graph, the levels of urbanization refer to the average number of addresses per square kilometer. Very high means over 2000, high means 1500-2000, moderate means 1000-1500, low means 500-1000 and none means 500 or less. Noticably, public transport use decreases as urbanization decreases. Car use as a driver steadily increases, with the other modes of transportation staying relatively constant.

The reason urbanization relates to increased e-bike use, is due to the availability of public transport, leading to lower car ownership rates Ling et al. [2015]. With the increased mobility options in urban areas, shifting to e-bikes is not as necessary compared to rural areas, where the car use is the dominant mode of transportation, also shown in figure 2.1. Therefore, substitutions to e-bikes is more likely to occur in rural areas Plazier [2022].

For car ownership, the literature has mixed results. Some studies suggest complementation in relation to e-bike use Plazier [2022], with car ownership being an indicator for e-bike adoption. Other studies suggest no difference in car ownership after e-bike adoption Kroesen [2017], and another suggests car ownership goes down slightly Sun et al. [2020]. Therefore, it was chosen to further investigate this factor.

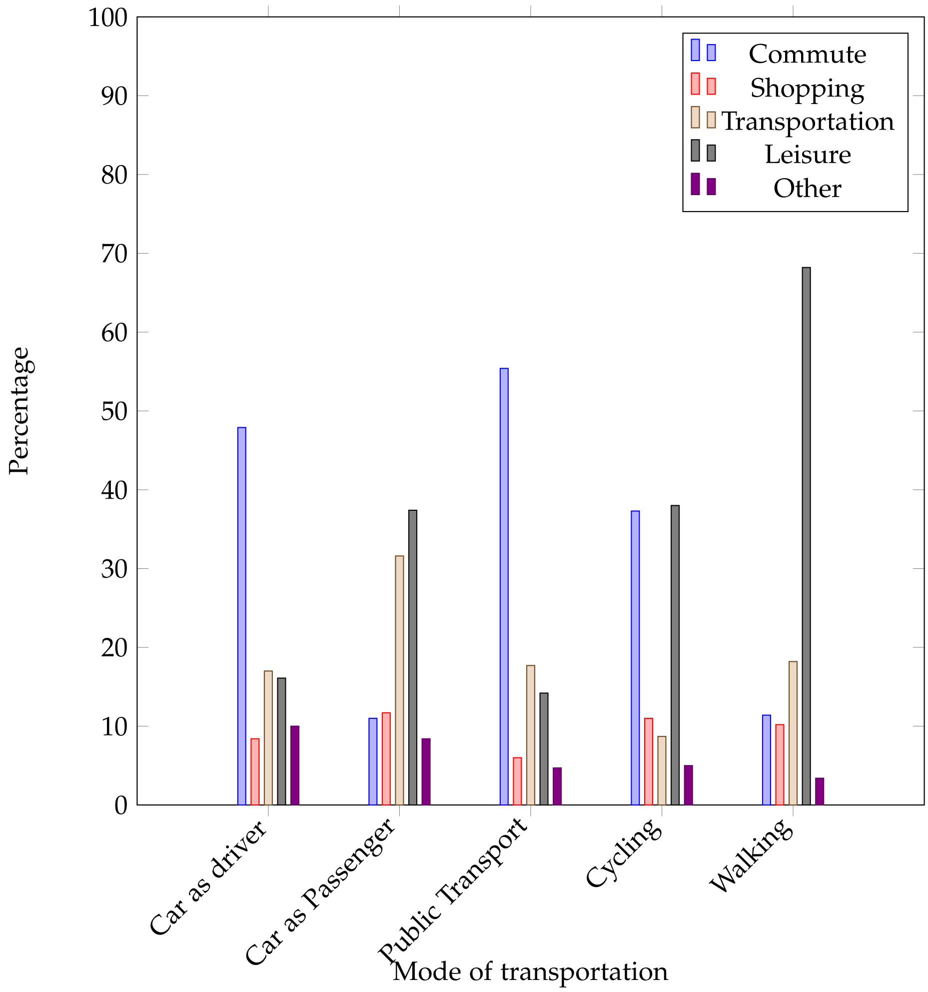


Figure 2.2: Transport modes share in relation to trip purpose CBS [2020]

The trip purpose has significant impact on the preferred mode of transportation. As shown in figure 2.1, cars are used more for commuting, cycling is done more frequently for leisure. The purpose of transportation refers to a number of different activities, such as deliveries of goods, visitation or self-care. Commuting includes going to and from work or educational courses, as well as going on business trips and professional driving.

The trip purpose affects e-bike use, as the e-bike purchase is usually associated with its intended use. Most studies find utilitarian reasons, such as commuting to work or education, to be more significant than leisure ones Kazemzadeh and Ronchi [2022] de Haas et al. [2022]. With the exception of elderly leisure trips Cherry et al. [2016], it is concluded that most leisure trips are still done by car. Comparing the literature to figure 2.2, it is shown that cycling trips have a large share of commuting and leisure, but only commuting is likely to have a significant impact. Therefore, it is hypothesised that commuting and shopping trips will have the biggest impact.

2.3 Stakeholder Analysis

2.3.1 Government

The institution within the Dutch government responsible for policy regarding e-bikes and modal shift is the ministry of infrastructure and water management. Due to the clear health benefits Oja et al. [2011], the ministry is heavily promoting cycling through several policies. In the ministry's book publication 'Cycling and Dutch national infrastructure' (2020), it mentions that the increase in e-bike use has led to some cities experiencing trouble with traffic flows on cycle paths. To maintain road safety, the current infrastructure demands adjustments. The ministry's aim is to resolve mobility issues and to relieve bottlenecks. In practice, this results in incorporating cycling demands in projects to contractors.

Another policy of the ministry is to promote cycling for children. In a report by Mobycon [2022], in assignment for the ministry, it addresses mobility poverty in the context of cycling. Also, the ministry is promoting e-bikes by financing e-bike businesses Sustainable Finance Lab [2022], in an effort to stimulate circular business-to-business initiatives.

2.3.2 E-bike Companies

For the e-bike industry, the emergence of e-bike use has been lucrative in this decade, with the global e-bike market being valued at 18 billion US Dollars in 2022. However, this wasn't always the case. In the 1990s, when electric bikes weren't as reliable, retailers in China wouldn't risk their reputation as frequent glitches would occur Yang [2010]. Later, in the late 2000s, e-bike marketing studies targeted mostly women, elderly Das and Pal [2009] and high-earning families Akhtar et al. [2014].

The e-bike market really took off when companies saw its potential. A study on one of the leading e-bike firms in China, performed by Ma et al. [2022], came to the following conclusions. Due to the technological advancements, modifications and amendments could be made to better adapt to the domestic market's needs. For example, a speedy-feeling products with more streamlined design were developed for younger consumers. Therefore, e-bikes could be marketed more efficiently.

In the Netherlands, the sales have increased significantly. In figure 3.5, the sales over the past decade, for new e-bikes and traditional bikes, are shown Rijwiel en Automobiel Industrie Vereniging [2022]. Note that the total volume of bicycle sales has steadily dropped from 1.2 million to about 900.000 from 2010 to 2021 respectively.

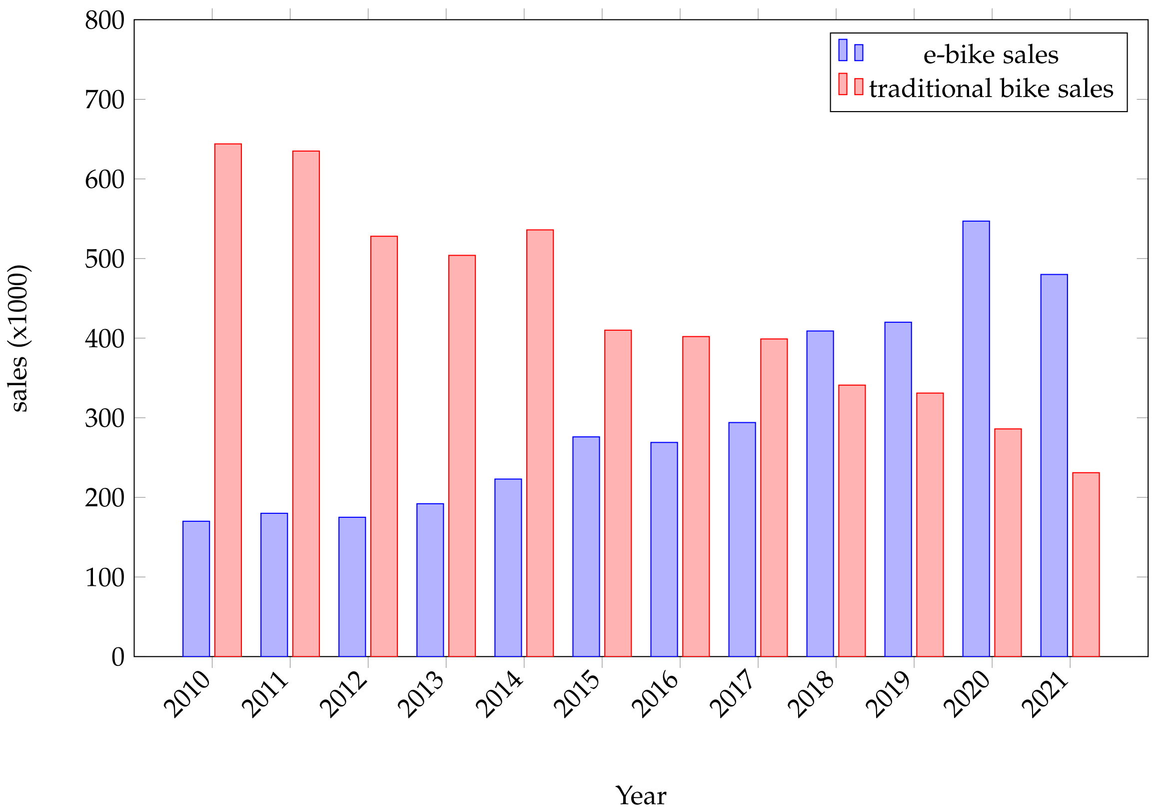


Figure 2.3: E-bike sales in the Netherlands Statistica Research Department [2022]

2.3.3 Travellers

As road users can be divided in several different ways, the most appropriate way highly depends on purpose of application Haustein and Hunecke [2013]. In this research, it is important to identify the strengths and weaknesses for e-bike use. Therefore, to further analyse the Dutch transport demographics of chapter 3.1 for this research, the following distinction will be made: the e-bike user and the non-e-bike user.

E-bike user

Initially considered as a tool for the elderly, this image slowly changed throughout the 2010s Engelmoer [2012]. As it reduces the barrier of topography MacArthur et al. [2014], it enables cycling for groups of people with physical limitations. For example, people with health problems or elderly cycle more on e-bikes than on traditional bikes Wolf and Seebauer [2014]. The image of e-bikes by e-bike users has been studied by Simsekoglu and Klöckner [2019b], with the main attitudes being that it led to increased health, contributed to improved self-image, and it was functional in daily life.

In another study, by Mildestvedt et al. [2020], it was found that the moderate physical activity from e-bikes led to feelings of joy and led to additional physical activity in their leisure time. Other perceived benefits, as studied by Jones et al. [2016], include feelings of freedom and relaxation, and in lesser form social activism. The environment being a lesser reason for e-bike adoption was also found by Simsekoglu and Klöckner [2019a], with symbolic benefits such as 'being proud of owning an e-bike' being a more important reason.

Studies by An et al. [2013] and Wolf and Seebauer [2014] note that e-bike users tend to have the following characteristics. They are generally in the high earning income classes and . Also, women are more likely to own e-bikes compared to men. The most common trip purposes are commuting and shopping, and trip length is generally short; most trips are made between 0-10km, with a travel time of up to 40 minutes. Most e-bike users live in highly urbanized areas.

Non-e-bike user

Despite the benefits, there are several barriers and limitations holding back large groups of travellers. As researched by Jones et al. [2016], in the United States, the biggest barriers to adopting an e-bike are income and the lack of appropriate infrastructure. In the Netherlands, however, the infrastructure for cycling is not as much of a barrier. A study by Hull and O'Holleran [2014] found the Dutch infrastructure to score highly among factors such as road safety, comfort and directness. Income is an important barrier, as the prices for e-bikes are more expensive compared to traditional bikes.

Other factors that limit e-bike use include poor weather or road conditions, the weight, and the fear of the e-bike getting stolen, as found in a study by Simsekoglu and Klöckner [2019a] in Norway. Another important barrier is the additional safety risks. With higher speeds, the risk and severity of an accident increases Schepers et al. [2018]. This is particularly apparent among elderly adopters, as the odds ratio for accident proneness increases significantly.

Other surveyed barriers are the limited battery and lack of battery charging stations Simsekoglu and Klöckner [2019a]. Other studies about the image of e-bikes found that using pedal assistance is in some way 'cheating', and reduces the health benefits that would have been obtained with a traditional bike Jones et al. [2016]. Additionally, it was found that the image of e-bikes leads to social barriers, with the perception that an e-bike is meant for old people.

2.3.4 Stakeholder diagram

In the Figure 3.4, the stakeholders are shown in the stakeholder diagram, visualising their influence and interest. The interest of the government is moderate, as the ministry is policing and promoting e-bikes. The e-bike industry has very high interest and moderate influence, as they are shaping the e-bike market. Individually, travellers have little influence on the modal shift to e-bikes, but understanding their motives is key to predicting the future trends.

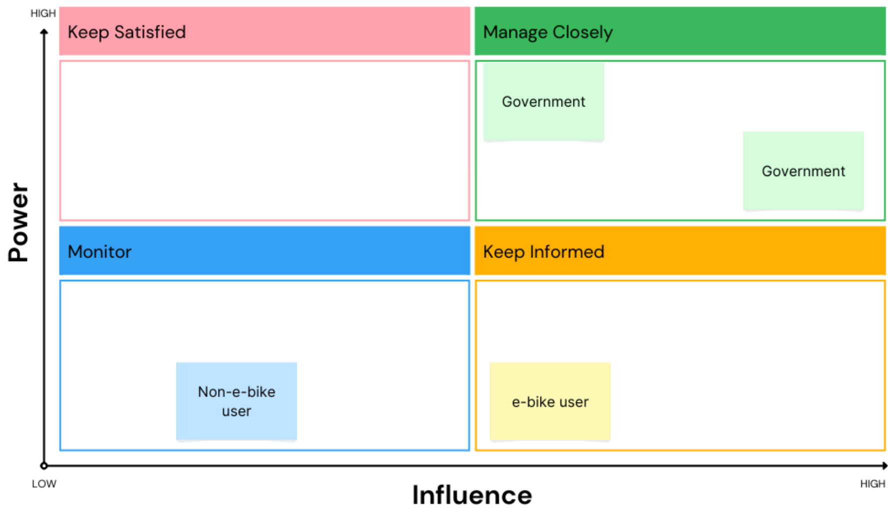


Figure 2.4: Stakeholder diagram

3 Methodology

In this chapter, the methodology is discussed. In section 3.1, the data collection is discussed. In section 3.2, the hypotheses found by the literature study are discussed. In section 3.3, it is explained how the data is applied and analysed, what the data looks like, and which variables were used. In section 3.4, the conceptual model is presented, on which the statistical tests can be applied. These are explained further in section 3.5.

3.1 Data collection

The data that will be used in this research will be from the Dutch Mobility Panel (MPN). The MPN consists of five research instruments: four questionnaires and a travel diary. The data includes personal characteristics, travel data and travel modes for approximately 2500 households every year Hoogendoorn-Lanser et al. [2015]. The questionnaire data falls under four categories: car data, mobility data, personal characteristics, and opinions on travel modes. Car data includes characteristics such as build, weight and constructing year. Mobility data includes other mobility accessibility, such as e-bike and bicycle ownership. Personal characteristics includes a lot of data, most importantly gender, age, employment, and education level. Finally, opinions on all modes of travel and all preferred modes for certain destinations are also included. The travel diary requires participants in a household to log all of their travels for three consecutive days in a year. This includes both travel time and travel mode. A household participates for four consecutive years. In this way, data on e-bike usage can be collected.

3.2 Hypotheses and Approach

After reviewing the literature, the main factors of the modal shift to e-bikes in the Netherlands that will be considered in this research are trip length, car ownership, urbanization, and trip purpose. Even though other factors such as gender, age or income have an effect, it is beyond the feasibility of the study. To further narrow down the research, walking as a transport mode is ignored, as its addition creates very limited effects. Therefore, the hypotheses are as follows:

1. E-bike adoption will impact the use of traditional bikes, cars, e-bikes and public transport trips.
2. Short trips (15 km and shorter) will be impacted more significantly than long trips.
3. Car ownership will go down as e-bikes are adopted.
4. E-bike usage will increase more significantly in lesser urbanized areas.

5. Trips for commuting and shopping purposes will be impacted by e-bikes more significantly than for other purposes.

6. E-bike usage will increase more with lower education levels.

As the participants participate for four years in a row, the research group will be the households that own an e-bike in the current year but didn't own an e-bike in the previous year. Additionally, their answers in the questionnaires will give insight into their travel characteristics. To determine whether the research group is representative of the Dutch population, comparisons in modal split must be made. A sample of non-e-bike owners will be investigated on the hypotheses to compare the results.

3.3 Data application

The answers from the surveys were submitted into several SPSS data files. Each question leads to a numerical value in the 'personal characteristics' data set. Binary questions lead to variables with either 3 or 4 possible values. For example, the question 'Do you own an e-bike' leads to the variable PEBIKE, which has 4 possible values. 0 for no, 1 for yes, 2 for does not own any vehicle, and 99 when the participant did not fill in this particular question. Other questions. such as 'What is your age', lead to a categorical numerical value, with 1 being under 12 years old, 2 for between 12 and 17 years old, and so on. These questions are linked to a personal id and a household id to identify the participants. The household id is also relevant, as some data, such as urbanization, is only stored in the household specific data set. For the data analysis, a python script was used to evaluate these variables.

The trip information variables are stored in the 'travel diary' data set, consisting of several components. Each trip has its own trip number, and has the information on the distance, vehicle type, purpose, among other variables. Such a trip is linked to a personal id, so that a participant can have multiple trips in the data set. Variables such as distance are stored multiple times, once as a numerical value representing the actual distance, and once as a categorical value representing the distance category (0-5km, 5-10km etc.). Additionally, the GPS data was used to correct divergent data filled in by the participants. However, only when the difference between these two values was too significant, it was corrected to the GPS data. To ensure the use of the most reliable data, the data with this GPS correction was used. For the transport mode and trip purpose variables, categorized and uncategorized versions are stored to limit the number of variations.

To measure the effect of the e-bike adoption, the following approach was used. First, the survey participants that filled in that they did not own an e-bike in the first year, but did own an e-bike in the second year were targeted. This means that this happened in three separate occasions, from 2017 to 2018, from 2018 to 2019, and from 2019 to 2020. Their data is combined for each hypothesis. The following formula was used to calculate the share of each transport mode for passenger kilometers and number of trips respectively.

$$A)N_n = \frac{\sum_n^{i=1} s_i}{\sum s_t ot} * 100\%$$

$$B)N_n = \frac{\prod_n^{i=1} i}{\prod x_t ot} * 100\%$$

Where n represents the individual transport mode, and i the number of trips of the respective transport mode. The parameter N represents the share of each transport mode, and s the distance travelled per trip. In equation a, it is divided by the sum of the total distance, and in equation b by the total amount of trips.

3.4 Conceptual model

In this section, an overview of all the most relevant factors is shown in figure 2.1. This model is inspired by the research on modal shift by Kroesen [2017], as it includes most of these factors in a statistical equations model.

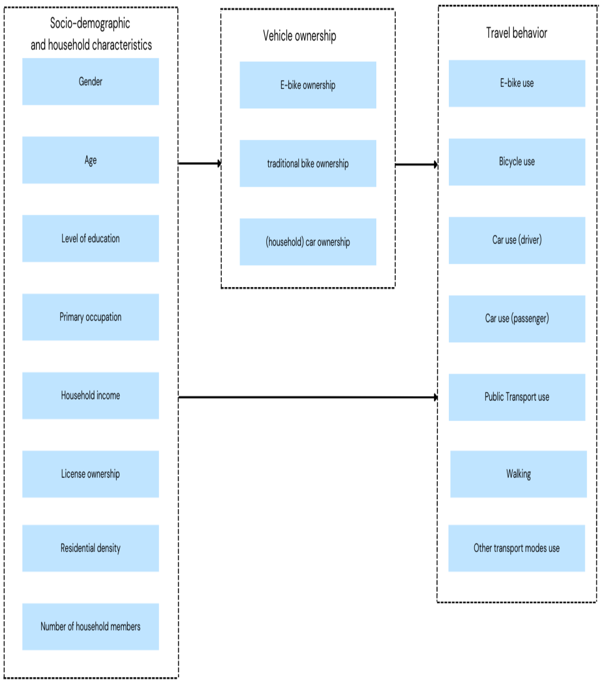


Figure 3.1: Complete conceptual model of modal shift to e-bikes

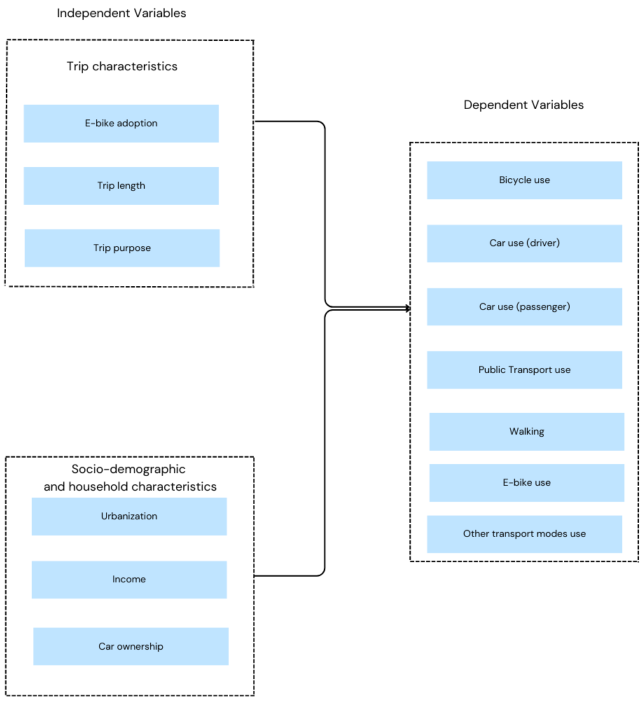


Figure 3.2: Conceptual model used in this research

In this research, the hypotheses are more specified, and therefore the conceptual model is simplified. The model used in this research is shown in figure 3.2. As the literature suggests, household characteristics are the independent variables. This means that it is expected that these factors influence e-bike and other transport mode uses. Therefore, these transport modes are the dependent variables. Across all hypotheses, the e-bike adoption from year 1 to year 2 is applied, and other independent variables are added for each hypothesis to specifically analyse these factors.

3.5 Statistical tests

To answer each hypothesis, several statistical tests must be performed to calculate whether the effects are significant. As the variables for each hypothesis are different, different tests must be applied. Below, a list for each variable is given, after which an explanation for each test will be given. To avoid falsely rejecting H_0, a significance level of 95% was chosen.

Hypothesis number+description	Number of variables	Variable type	Data type	What is being tested	Required test
1, modal shift	2	Both dependent	Continuous	Differences between T0 & T1	Paired T-Test
2, trip length	2	Both dependent	Categorical	(Expected) frequencies	Chi Squared test
3, car ownership	1	dependent	Nominal	(Expected) frequencies	Chi Squared test
4, urbanization	2	Both dependent	Categorical	Differences between T0 & T1	Chi-squared test
5, trip purpose	2	Both dependent	Categorical	Differences between T0 & T1	Chi-Squared test
6, education level	2	Both dependent	Categorical	Differences between T0 & T1	Chi-Squared test

Table 3.1: Statistical tests for hypotheses

As shown in Table 3.2, the two required statistical tests are the paired T-Test and the Chi-Squared test. In the next section, the application for the hypotheses and formulae are explained. These tests are done using Python, and only significant results are shown.

3.5.1 Paired T-test

To determine whether the mean difference between two sets of observations is zero, a paired T-test is required. In this research, this is necessary as the modal shift data as each transport mode use is compared to the variable of e-bike use. The test statistic follows the t-distribution, with degrees of freedom in the following formula, after which the mathematics table can be ensued.

$$v = n - 1$$

$$t = \frac{(D - \mu_D)}{s_D / \sqrt{n}}$$

Where D denotes the mean difference between the samples, and μ_D is the expected difference. Under the null hypotheses, this means that $\mu_D = 0$.

3.5.2 Chi-Squared test

The Chi-Squared test is used to test whether two variables are connected. Both variables need to be categorical, where the sampling distribution of the test statistic follows the theoretical chi-square distribution. When the observed and expected cell frequencies are the same in every cell, the distribution apparently is coincidental, and the distribution criteria of the variables are independent of each other. For the data in this study, it is applied to all categorical (or nominal) data such as trip length categories, and comparing the before and after frequencies and expected frequencies.

$$\chi^2 = \sum_{i=1}^{r} \sum_{j=1}^{c} = \frac{(O_i j - E_i j)^2}{E_i j}$$

To compute the confidence interval, a critical value must be chosen. This has two variables, α^2, the level of significance, and v, the degrees of freedom. The level of significance is chosen based on the test, and the v has the following formula. This obtains the critical value $\chi_v \alpha^2$, which can be read from math tables.

$$v = (r - 1)(c - 1)$$

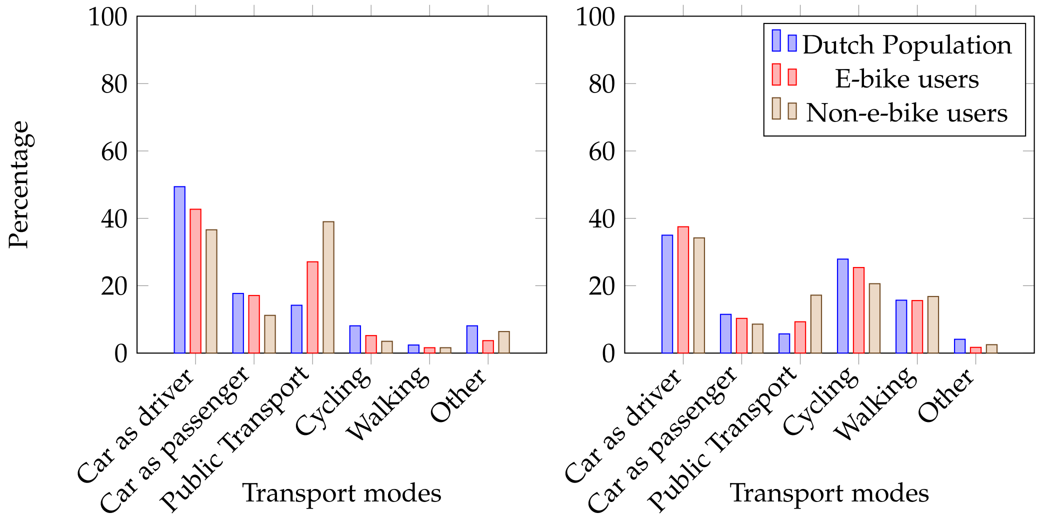
With r and c as number of rows and columns respectively.

4 Data analysis

In this chapter, the results of the data analysis are shown. In section 4.1, the demographics of the target group and the control group are shown. In sections 4.2 to 4.7, the results of the individual hypotheses are discussed.

4.1 Demographics

Across the MPN surveys (2017-2020), 424 new e-bike users emerged. Also, a random sample of 5000 people were chosen to act as a control group. This was done to test whether the target group both conformed with the Dutch population, as well as the average of the survey participants. First, the characteristics of both the target group and control group are shown in figure 4.1 and table 4.1. The use of 'other' modes of transportation refers to a long list of transport modes, including scooters, agricultural vehicles, campers, boats (scheduled services or ferries), roller skates and so on. As this list is so diverse, not many conclusions for these modes can be made. Additionally, this mode is not always included in the available data.



(a) Passenger kilometer

(b) Number of trips

Figure 4.1: Transport mode shares

Note that some totals don't exactly add up to 100%, as some questionnaires were not filled out fully. However, this happens very rarely, and only leads to deviation of around 2%, and therefore their results were considered. Noticably, the share of public transport for both

Demographics		E-bike users	Non-e-bike users
Gender	Male	42.7%	44.8%
	Female	57.3%	55.2%
Age	12-17	3.3%	4.8%
	18-24	2.1%	7.4%
	25-29	5.9%	7.6%
	30-39	15.6%	20.0%
	40-49	12.7%	14.0%
	50-59	23.3%	16.3%
	60-69	22.5%	16.0%
	70-79	12.5%	11.6%
	80+	2.1%	2.2%
Education Level	Low	28.3%	17.6%
	Middle	38.2%	34.9%
	High	33.4%	33.9%
Urbanization	Very Highly	17.6%	23.8%
	Highly	29.2%	30.6%
	Moderate	17.9%	18.2%
	Low	25.4%	19.4%
	None	9.7%	8.0%
Car ownership	None	21.4%	29.8%
	At least one	78.6%	67.8%

Table 4.1: Demographic Data

the target group and the control group is significantly higher than for the Dutch population when taking into account the passenger kilometers. This can somewhat be explained by the fact that a large portion of the participants of the survey live in very highly or highly urbanized areas, as shown in Table 4.1, and they tend to use more public transport, as shown in figure 3.2. However, sample variability also plays a role, though the number of participants is relatively high compared to other studies. As for the number of trips comparison, the share of public transport is still relatively high, but most of the other transport modes conform relatively well. Therefore, the results of the transport mode share of the number of trips is expected to be more conforming with the Dutch population compared to the passenger kilometers.

4.2 Modal shift

For the modal shift, the data of the target group is analysed. Fist, their transport mode usage of the year before they adopted an e-bike is displayed as 'year 1'. The year of e-bike adoption is 'year 2'. It was hypothesised that e-bike usage would increase, and all other transport mode usages would decrease.

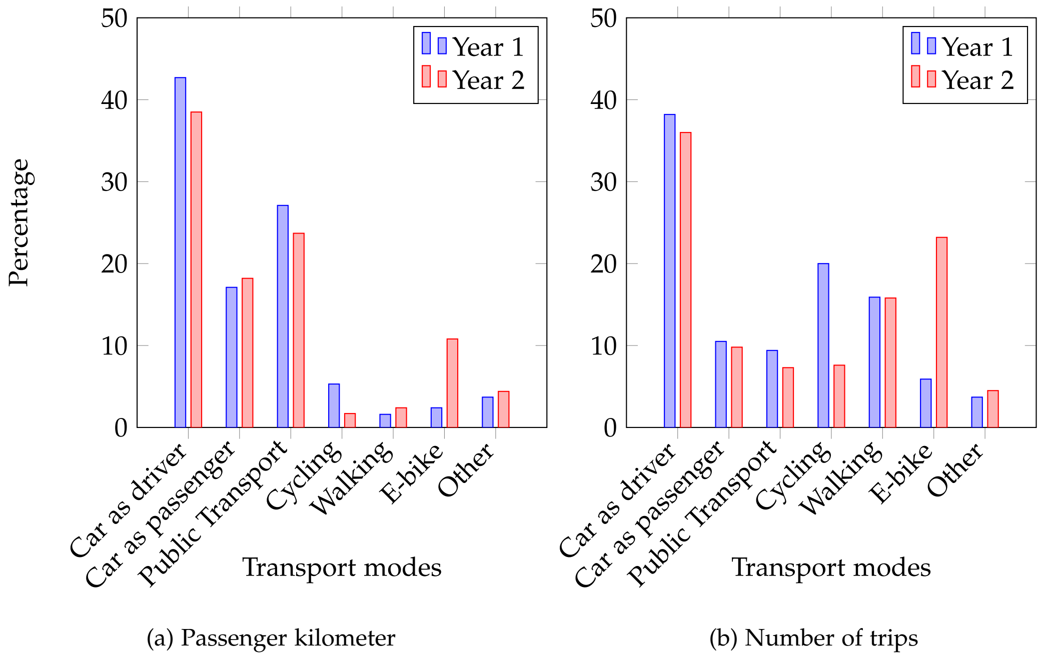


Figure 4.2: Transport mode shares before and after adopting e-bikes

Figure 4.2 shows slight decreases in both car use as a driver and public transport use in terms of share percentage of total passenger kilometers. This indicates that after e-bike adoption, the new e-bike impacts modal choice behaviour for these transport modes. Note that this is not the case for car as a passenger and walking, as it slightly goes up. The strong decrease in cycling compared to the increase in e-bike use suggests heavy correlation, as it decreases from 5.2% to 1.8%.

For the number of trips, a more significant increase in e-bike use can be found. However, this only manifests itself in the sharp decrease in cycling, suggesting only traditional bikes are replaced to a significant amount. In the table, all the relevant P-values are given.

Transport mode	P-values	
	Passenger kilometer	**Number of trips**
Car as driver	P ¡ 0.05	.
Car as passenger	.	.
Public transport	.	.
Cycling	P ¡ 0.001	P ¡ 0.001
Walking	.	.
Other	.	.

Table 4.2: P-values for modal shift

4.3 Trip length

For trip length, once again the data from before and after e-bike adoption is analysed. It was hypothesised that e-bike trips will account for a larger share of shorter trips (0-15km) compared to longer trips. It was chosen to only display the data as a share of the total number of trips that ended in each respective distance group for each transport mode. Calculating the share in terms of passenger kilometers would only affect the longer distance categories, which are most unlikely to be affected by e-bike modal shift.

Distance	**Car as driver**		**Car as passenger**		**Cycling**		**E-bike**	
	Before	**After**	**Before**	**After**	**Before**	**After**	**Before**	**After**
0-5km	27.1	26.5	5.9	6.2	30.6***	11.4***	7.2	28.6
5-10km	54.6*	46.0*	14.6	11.0	12.9***	3.0***	4.8	23.5
10-15km	55.3	58.1	11.7	11.7	6.3*	2.4*	9.2	19.1
15-20km	56.1*	44.8*	13.3	20.6	4.5*	0.9*	3.7	18.7
20-30km	57.0	68.5	20.5*	12.5*	1.9	2.0	5.1	7.0
30km+	38.1	37.3	18.2	18.6	1.4	0.7	0.3	4.6
Distance	**Public Transport**		**Walking**		**Other**		**E-bike**	
	Before	**After**	**Before**	**After**	**Before**	**After**	**Before**	**After**
0-5km	1.4	1.1	27.3	25.4	0.3	0.5	7.2	28.6
5-10km	9.0	9.0	2.6	5.7	1.4	1.6	4.8	23.5
10-15km	14.5*	6.9*	0.7	0.8	2.1	0.8	9.2	19.1
15-20km	20.8*	13.3*	0.4	1.4	1.1	0.0	3.7	18.7
20-30km	11.2	8.5	1.4	0.5	2.8	1.0	5.1	7.0
30km+	33.8	33.8	0.3	0.5	7.5	4.3	0.3	4.6

Table 4.3: Number of trips in trip length, as share of total (Number of trips)

(a) * indicates P ¡ 0.05, *** indicates P ¡ 0.001

As shown in Table 4.3 and as expected from Table 4.2, e-bike use has the most significant impact on cycling. In terms of trip distances, this also shows itself in the shorter distances, as trips ¡15km have a significantly more impact compared to longer ones. This is most likely due to the fact that there are generally more trips to be replaced by e-bikes, as the majority of trips are below ¡15km, which can be shown in the e-bikes' column.

As the variables are dummy coded, the Chi-squared test was applied to each before and after transport mode use to test for statistical relevancy. Noticably, walking and car use as a passenger once again remain relatively stable, with one exception in the 20-30km section for car passengers. This is most likely an outlier, as the other values are quite stable. For public transport, a significant decrease in use is noticed in the medium length (10-20km) brackets, suggesting e-bikes make for a useful replacement within these distances. It should be noted that for shorter trips, public transport is barely used, as short public transport trips are generally inconvenient as trip duration is relatively long. For longer distances, however, the transport share remains stable, suggesting a cut-off point where public transport is more useful as opposed to e-bike use, for the average traveller.

4.4 Car ownership

For car ownership, it was hypothesised that it would go down after e-bike adoption. Additionally, over a longer period of time, this effect should be more noticeable. It is chosen to only investigate the ebike adopters from 2017 to 2018, as they would have a longer period on which to (dis)own a car. However, this leads to a smaller sample size.

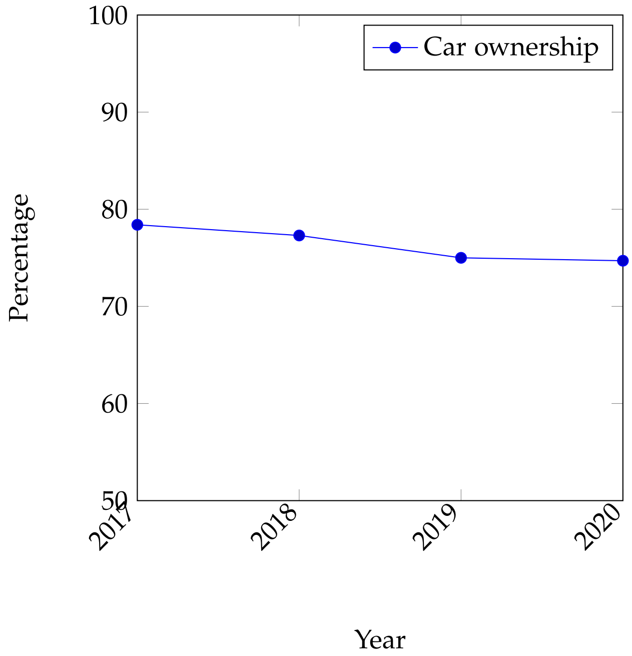


Figure 4.3: Car ownership of new e-bike adopters

As shown in Figure 4.4, the car ownership drops slightly from 78.4% in 2017 to 74.7% in 2020. The result is not significant enough to be statistically relevant, as the χ^2 = 0.39 and the p-value is p=0.90. However, as anticipated, the impact on car ownership is a long-term phenomenon. In other studies, it is generally discussed over 1 year Sun et al. [2020]. Therefore, it was hypothesised that 4 consecutive years could be enough to show statistical relevance, but this is not the case.

4.5 Urbanization

For urbanization, it is chosen to compare the share of the e-bike use to the expected share of the Dutch population for each urbanization level. As only data of the Dutch population on passenger kilometer for urbanization can be found, this was also used for the e-bike users. The data on e-bike users after e-bike adoption were used. To check for statistical significance, a chi-squared test was used. The reason urbanization was not analysed according to all transport modes, is due to the low sample size.

Urbanization level	**Passenger kilometer**	
	Non e-bike users	**E-bike users**
Very Highly	25.3*	35.2*
Highly	29.7	21.3
Moderate	16.3	15.9
Low	21.3	15.4
None	7.3*	12.2*

Table 4.4: E-bike adoption per urbanization level

(a) * indicates P¡0.05

Even though the increased use of e-bikes in sparsely populated areas was hypothesised, this is only partly the case. Only in the very high and very low categories, an increase in e-bike use is noticable. This means that, as hypothesised, the e-bike becomes a viable option in low-urbanized regions where fewer transport mode options are available. The very high urbanization level increase could also be explained by people unwilling to go with public transport, as Table 4.3 also suggests.

4.6 Trip purpose

Next, the trip purposes for each transport mode before and after the e-bike adoption are investigated. It is expected for commuting and shopping to have a high e-bike usage share. The percentages are a share of the total number of trips for each purpose. To check for statistical relevance, a chi-squared test was used for each transport mode before and after e-bike adoption.

Trip purpose	Car as driver		Car as passenger		Cycling		E-bike	
	Before	After	Before	After	Before	After	Before	After
Commuting	24.6	25.1	6.3	4.4	30.3***	12.2***	6.7	26.5
Shopping	60.7*	42.8*	14.7	14.4	8.3*	3.8*	3.2	22.9
Leisure	55.0	55.5	15.8	16.9	2.9*	1.5*	3.3	10.9
Transportation	48.4	44.5	9.8	11.9	19.1***	4.9***	8.5	29.0
Other	32.4	31.5	20.4	18.9	1.3	0.3	0.3	4.8
Trip purpose	**Public Transport**		**Walking**		**Other**		**E-bike**	
	Before	**After**	**Before**	**After**	**Before**	**After**	**Before**	**After**
Commuting	1.4	1.8	30.0	29.4	0.6	0.4	6.7	26.5
Shopping	10.7	11.0	1.2	3.0	1.2	2.1	3.2	22.9
Leisure	18.6*	11.7*	0.8	0.8	3.5	2.7	3.3	10.9
Transportation	7.5*	2.9*	5.8	5.8	0.9	1.0	8.5	29.0
Other	38.0	41.7	0.3	0.7	7.2	2.0	0.3	4.8

Table 4.5: Trip purposes of each transport mode as a share of the total number of trips

(a) * indicates P ¡ 0.05, *** indicates P ¡ 0.001

Again, traditional bikes are replaced by e-bikes across all purposes. Most notably, e-bike use increases significantly for the purposes of shopping and commuting, as hypothesised. Car use as a driver is significantly has a significantly lower share after e-bike adoption, suggesting a big impact for e-bikes. Additionally, public transport has significantly lower shares for leisure and transportation, not expected by the hypotheses. The other modes, car as a passenger and walking, are largely unaffected.

4.7 Education level

Finally, the education level for each transport mode before and after the e-bike adoption are investigated. It is expected for that lower education levels adopt more e-bikes, and therefore have a bigger impact on other transport modes. To check for statistical relevance, a chi-squared test was used for each transport mode before and after e-bike adoption.

Education level	Car as driver		Car as passenger		Cycling		E-bike	
	Before	After	Before	After	Before	After	Before	After
Low	34.4	28.6	20.9	21.0	7.5*	3.5*	3.7	11.9
Moderate	48.2	46.9	18.8	17.0	6.4*	0.7*	2.7	12.7
High	41.7	36.7	14.0	17.4	3.1	1.7	1.6	8.4
Trip purpose	**Public Transport**		**Walking**		**Other**		**E-bike**	
	Before	After	Before	After	Before	After	Before	After
Low	21.2	32.2	3.1	2.7	9.3	0.1	3.7	11.9
Moderate	19.9	10.7	1.7	3.1	2.2	8.7	2.7	12.7
High	36.1*	30.9*	1.0	1.6	2.8	3.1	1.6	8.4

Table 4.6: Use of each transport mode as a share of the total passenger kilometers, subdivided for each education level

(a) * indicates P ¡ 0.05

5 Conclusions

This research has attempted to provide insights on the increasing usage of e-bikes and the factors contributing to this phenomenon in Dutch context. The end result is a combination of a literature study and a data analysis.

5.1 Literature conclusions

By analysing the Dutch transportation usage, it was found that a large number of factors contribute to the choice of transport mode by the Dutch population. Age, gender, income, education level, urbanization and trip purpose all heavily influence modal choice. In respect to the e-bike emergence, this means that e-bike owners in the past were generally of older age, but recently e-bikes have been adopted through the age groups more evenly. Still, women are more likely to own e-bikes, as well as a high income is probable.

Additionally, reasons for adopting an e-bike have changed from solely practical motives like overcoming topography barriers, to additional symbolic motives. These motives include increased health and increased self-image. This is due to the changed positive image, as stigmas have decreased. However, the stigma has not disappeared, as the idea of e-bikes being 'cheating' or 'only for elderly' is still experienced. Other barriers include weight, income, and higher safety risks.

Other factors have come from the stakeholders, namely the government and the e-bike market. The government is mainly responsible for creating the infrastructure required for the prevalent biking culture in the Netherlands, as well as several initiatives promoting e-bikes. The e-bike market is heavily responsible for popularizing and normalizing the use of e-bikes. Due to technological advancements, e-bikes have become reliable enough to convince the general public of its perceived benefits, after which marketing has increased it even more.

5.2 Data analysis conclusions

The data analysis was done to examine whether the e-bike increase leads to the replacing of other transport modes. The data of the Dutch Mobility Panel was tested on modal shift, trip length, car ownership, urbanization and trip purpose, in terms of passenger kilometer and number of trips. The results indicate that e-bikes replace traditional bikes, as expected in the existing literature. The other hypotheses are inconclusive, as the results do not conform to the expected results from literature.

6 Discussion and recommendations

By examining a group of e-bikers' travel behavior before and after adopting an e-bike, this study provides a better understanding of the overall modal shift. For the literature study, a broad image was analysed and put into Dutch context. However, a significant number of the expected factors were inconclusive in this study.

This study relates to the works of de Haas et al. [2022] and Sun et al. [2020], as they have worked with the MPN data as well. The study of Sun (2020) has several key findings. The study investigates e-bike use after e-bike adoption, and tests it on an aggregated level on the factors age, gender, trip length, trip purpose, and urbanization. This study intended on confirming the findings of Sun (2020) in the new available data, as well as extending on it by exploring different factors, such as car ownership and education level. Additionally, the methodology chosen led to a significantly smaller target group compared to this study, as only 107 participants as opposed to 424 participants were analysed.

The study of de Haas (2022) differs significantly to this study. In that study, a full model on trips is made to predict the amount of e-bike and car trips, based on the mean and expected number of trips. Indicators to reveal different e-bike user groups for all characteristics is done, leading to results with multiple variables. For example, it was indicated that 53% of users are retired older leisure users. Through this method, a larger sample size was obtained. However, with this method, the results are more general, compared to specifically new e-bike users that were investigated in this study. This means that individual characteristics can be spotted more clearly in this study. Additionally, only car use and e-bike use were considered, whereas the full modal shift was investigated.

One of the causes of the inconclusive results are the divergent survey demographics compared to the Dutch population. Even though the participants are mixed in terms of age and gender, their transport modes shares are very unlikely. The MPN chooses participants randomly, and the days to keep track of the travel diary are also random. Therefore, significant randomness does have an impact. Additionally, the relatively small number of e-bike adopters can magnify these problems. As their results are of most importance of this study, any discrepancies are detrimental for accurate results.

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