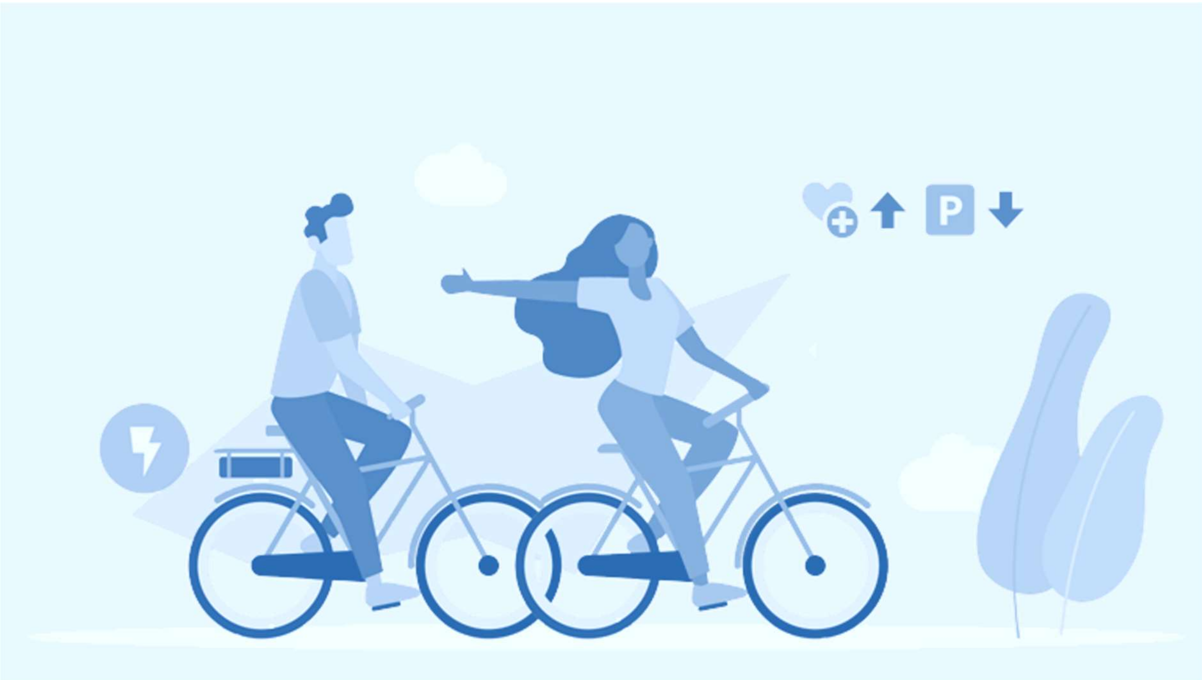
Master Thesis

MSc Complex Systems Engineering and Management

The Impact of E-bike Adoption on Dutch Mobility

A quantitative analysis of how vehicle ownership, e-bike purchases, and car attitude shape travel behaviour in the Netherlands



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The Impact of E-bike Adoption on Dutch Mobility

A quantitative analysis of how vehicle ownership, e-bike purchases, and car attitude shape travel behaviour in the Netherlands

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Preface

I am pleased to present this research paper of my master thesis, studying the impact of e-bikes on travel behaviour in the Netherlands. This thesis was written as finalisation of the master's degree in Complex Systems Engineering and Management at TU Delft.

I would like to express my sincere gratitude to Maarten Kroesen and Nihit Goyal for their guidance, support, and encouragement as my supervisors throughout the development of this master's thesis. I appreciated your patience and understanding throughout this process.

I would also like to thank to my girlfriend, friends, family, and fellow students. Their support throughout my master's journey, which ultimately led to this thesis, played a crucial role in helping me successfully to complete it.

Happy reading,

Huub van der Meulen

October 2024

Summary

The Netherlands has experienced a notable rise in the use of electric bikes (e-bikes), with their share of cycling trips increasing from 8% in 2013 to 18% in 2019, resulting in over 700 million e-bike trips and more than 4.1 billion kilometres travelled. In 2021, e-bikes accounted for 52% of new bicycle sales, with about 23% of cyclists relying solely on them. While e-bikes are most popular among those over 65 for leisure, their growth is rapidly increasing among younger users, who predominantly use them for commuting. E-bikes have the potential to replace short car trips, which could lead to significant environmental benefits, given that cars emit substantially more CO_2 than e-bikes. However, it is crucial to determine whether e-bikes are truly replacing car trips or merely substituting conventional bikes. Understanding this substitution effect is essential for effective policy formulation and infrastructure planning to enhance cycling environments and promote healthier mobility.

In the Netherlands, e-bike ownership has significantly reduced the use of conventional bicycles, with a lesser impact on car and public transport use. While earlier studies, such as those by Kroesen (2017), indicated that e-bikes mainly substitute for conventional bikes rather than cars, findings by de Kruijf et al. (2018) highlighted that car owners are more likely to use e-bikes for car trips, particularly when dissatisfied with car commuting. Research also suggests that e-bikes hold potential for replacing public transportation, although high purchase prices remain a barrier.

This study aims to explore how attitudes influence the substitution effect of e-bikes on various transportation modes, considering the heterogeneous ways individuals use e-bikes. Additionally, it provides a temporal comparison of e-bike ownership's impact on travel mode use, offering fresh insights that could guide policymakers in promoting e-bikes to reduce reliance on more polluting transportation options.

The following research question are formulated:

- To what extent do bike, e-bike and car ownership influence the use of different modes, controlling for social demographic characteristics?
- To what extent does the purchase of the e-bike influence the use of different travel modes over time?
- To what extent does the attitude towards the car moderate the relationship between e-bike ownership and the use of different modes?

This research uses data of the Mobility Panel of the Netherlands (MPN) in order to analyse the data. With the Mobility Panel of the Netherlands (MPN), the KiM (Knowledge Institute for Mobility Policy) collects data on the travel behaviour of a fixed group of people and their households over several years (KiM, 2022). Data is used specifically from 2018 and 2019 to avoid pandemic-related disruptions.

This research employs two methodologies to address the research questions: cross-sectional regression analysis and the Difference-in-Differences (DID) method.

Cross-sectional regression analyses the relationship between e-bike purchases, social demographics, car attitude and travel mode usage at a specific point in time. This method is beneficial for policy analysis, offering insights into current influences on travel behaviour, and is relatively straightforward and efficient. However, it has limitations, such as assuming linear

relationships, relying on proper model specification, and lacking insights into temporal changes due to its single-point analysis.

Difference-in-Differences (DID) assesses the impact of e-bike purchases by comparing the average changes in travel mode usage for people who purchased an e-bike. This method helps establish causal relationships while controlling for unobserved, time-invariant confounders. Despite its strengths, DID relies on the parallel trends assumption and requires stable composition in treatment and control groups to avoid bias.

Three models are estimated in this research, comprising both cross-sectional regression analysis and the Difference-in-Differences (DID) method. The cross-sectional regression analysis is divided into four parts for 2018 and 2019: one part examines vehicle ownership as an independent variable affecting mode use, the second part focuses on socio-demographics influencing vehicle ownership, the third combines both ownership and socio-demographics, and the fourth includes attitudes. For the DID model, data from both years is analysed. SPSS is employed for the analysis. The socio-demographic data is adjusted using dummy variables, and distances travelled are aggregated for individual respondents, while a factor analysis is conducted on six attitude statements.

The first research question will be answered by the multiple regression analysis including vehicle ownership and travel behaviour (without attitude included), controlling for social demographics. In summary, e-bike ownership not only promotes e-bike use but also substitutes for conventional cycling and in lesser extent (to no extent) car use, highlighting its potential for encouraging more sustainable transportation choices.

E-bike is strongly correlated with e-bike ownership; owning an e-bike significantly increases its use, with no notable effect from car or bike ownership. Conventional bike use is positively associated with bike ownership, while negatively impacted by car and e-bike ownership. Car ownership significantly boosts car use, and e-bike ownership is negatively correlated with it, indicating e-bikes may reduce car travel. Conventional bike ownership shows an insignificant effect on car use. Car ownership is negatively correlated with public transport use, while conventional bike ownership positively influences public transport use, indicating potential multimodal travel behaviour.

When controlling for social demographics, results remain largely consistent, although e-bike ownership's effect on car use becomes insignificant, while the impact of car ownership is reduced. E-bike ownership emerges as the strongest predictor of e-bike use, indicating that it plays a pivotal role in determining travel behaviour. Additionally, students and individuals with higher education levels are more likely to use bikes, while car use is high among high-educated, employed males.

The following analysis, answering research question three, incorporates car attitudes to evaluate their direct impact on travel behaviour and their moderating effect on the relationship between e-bike ownership and travel behaviour. Overall, the analysis underscores the importance of car attitudes in shaping travel behaviour. E-bike owners' positive attitudes towards cars correlate with reduced e-bike usage, and car attitudes better explain bike use than e-bike ownership does. This suggests that the substitution effect of e-bike ownership might be weaker than initially assumed, with car attitudes providing a more comprehensive understanding of travel behaviour.

E-bike ownership remains the strongest predictor of e-bike use. However, a negative moderating effect of car attitude is observed. E-bike owners with a positive attitude towards cars tend to use their e-bikes less, indicating that such attitudes weaken the expected increase in e-bike use associated with ownership. E-bike ownership is no longer significant for bike use, while car attitude shows a negative correlation with bike use, suggesting that individuals with a positive car attitude travel less by bike. Evidentially, results show a positive effect of car attitude on car use. There is a negative correlation between car attitude and public transport use, indicating that those with a positive attitude towards cars tend to use public transport less.

The second research question uses the DID method and the paired t-tests to present the findings. Overall, these results highlight the nuanced effects of e-bike ownership on travel behaviour, particularly its substitution for conventional bike use, while car use remains unaffected by e-bike ownership changes. The DID shows no substitution of e-bike for conventional bike while the paired t-test suggest a substitution.

Again, an increase in e-bike ownership significantly predicts an increase in e-bike use, indicating that more ownership leads to greater distance travelled on e-bikes. However, changes in e-bike ownership do not significantly impact the use of cars, conventional bikes, or public transport. A significant finding is a decrease in conventional bike use among e-bike purchasers, indicating that purchasing an e-bike reduces conventional bike use. There was also a noted decrease in conventional bike use within this group. Interestingly, those who owned e-bikes in both years saw a significant decrease in e-bike use, while their conventional bike usage remained unchanged.

The discussion section of the study interprets the significance of the findings regarding e-bike ownership, car attitudes, and their influence on travel behaviour, placing these insights in the context of previous research while also addressing the limitations of the study.

An important finding is the negative moderating effect of car attitudes on e-bike use. E-bike owners who have a positive attitude towards cars tend to use their e-bikes less frequently. This challenges the assumption that pro-car attitudes would lead to increased e-bike usage as a substitute for cars, instead suggesting that positive car attitudes might diminish the potential substitution effect of owning an e-bike. Furthermore, this study indicates that the substitution effect of the e-bike is not straightforward. The findings suggest that while the e-bike does not appear to replace car usage, there is some evidence to support the notion that it may substitute for conventional bicycles.

The findings align with existing literature indicating that e-bikes primarily replace conventional bicycles rather than cars. However, this research adds a new dimension by emphasizing the moderating effect of attitudes, suggesting that understanding travel behaviour requires more than just examining ownership and usage patterns.

The research findings lead to several recommendations for enhancing policymaking and promoting sustainable travel behaviour. Firstly, while incentivizing e-bike ownership through subsidies is important, addressing the attitudinal barriers that maintain car dependence is crucial. Urban planners should focus on reshaping public perceptions about car use, particularly among car-dependent populations, alongside increasing e-bike infrastructure. Additionally, policymakers should consider the implications of helmet regulations and age restrictions on e-bike adoption, particularly for younger riders. These regulations could discourage e-bike use, it is important to consider the potential consequences. Given the strong link between e-bike ownership and usage, targeted financial incentives for commuters in suburban and rural areas could drive adoption and reduce reliance on cars.

Limitations of the study include the use of data from 2018 and 2019, which may not accurately reflect the current mobility patterns, particularly because of the surge in e-bike usage following from the COVID-19 pandemic, especially among younger users. The research also assumed uniform effects across individuals, potentially overlooking the influence of certain factors. Furthermore, the grouping of public transport modes may have diluted nuanced insights, and the sample's urban overrepresentation could bias the results.

Future research should be exploring the relationship between attitudes and e-bike use across various demographics could enhance understanding of travel behaviour and inform strategies to encourage e-bike adoption. Additionally, utilise current data to accurately capture transportation trends, employ methods that account for individual heterogeneity (such as fixed effects models), and differentiate between public transport modes for deeper insights.

Key words: E-bike, Travel behaviour, Substitution, Netherlands Mobility Panel (MPN), Difference-in-Differences (DID), Attitude

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1. Introduction

1.1 Problem definition

In recent years, the Netherlands has witnessed a significant increase in the popularity of electric bikes (e-bikes), marking a transformative shift in the landscape of mobility (Bright, 2022; Hackmann, 2023). In 2019, around 18% of cycling trips are made by an e-bike, compared to only 8% in 2013 (De Haas & Hamersma, 2020). This equates to over 700 million e-bike trips involving more than 4.1 billion km travelled by e-bikes. In 2021, about 52% of the 923,000 new bicycles sold were e-bikes (BOVAG-RAI, 2022). Remarkably, approximately 23% of cyclists rely only on e-bikes for their travels (Van Deemter et al., 2022). As these e-bikes become integral to daily commuting, it is relevant to find out what this means for mobility in the Netherlands.

The e-bike gained popularity in the early 2000s, particularly among individuals over the age of 65 (De Haas & Hamersma, 2020). Although the e-bike is still most popular among people aged 65+, the share of e-bikes is growing the fastest for the group under 65. Those two groups have divergent motives for using the e-bike. Individuals aged 65 and above primarily utilize e-bikes for leisure purposes, whereas younger demographics predominantly rely on them for commuting and education. The fat (e-)bike specifically is popular among young people because of the looks, the low price and the speed. However, a lot of policy makers have criticised the fat bike (KRO-NCRV, 2024; RTL, 2023). Especially in the cities, policy makers struggle with the challenges posed by the increasing use of the e-bike, particularly as they interact with other cyclists and other two wheeled vehicles in bicycles lanes (Kraniotis, 2021; RTV Utrecht, 2022).

The growing role of e-bikes is changing the daily lives of the Dutch population and holds the potential for creating significant environmental benefits. 50% of all car trips are under 7.5 km, and of all trips with a distance between 7.5 and 15 kilometres 70% go by car (Statistics Netherlands, 2016). According to research, acceptable distances for e-bike trips are a similar distance, with 58% of commuting trips being under 9.5 km (De Haas, 2023). The e-bike presents an opportunity to travel at higher speeds with minimum effort, thereby having the potential to replace a substantial part of the trips made by car. Considering that a car emits 40 times more CO_2 than an e-bike, substituting car trips with e-bikes could generate substantial environmental benefits while simultaneously mitigating congestion issues (Shao et al., 2012). E-bikes also occupy less physical space compared to cars, thus influencing spatial planning considerations. Additionally, e-biking is a more active mode of transportation than driving, promoting healthier lifestyles.

However, whether the e-bike really replaces cars is an important question. As the e-bike becomes a mainstream mode of transportation, figuring out if the e-bike replaces the car is relevant in order to understand the substitution effect. In fact, it would be a different situation if the e-bike replaced, for example, the conventional bicycle. If this were the case, the e-bike would actually be more harmful to the environment by having a battery compared to a conventional bike. Therefore, policymakers need to understand how the mobility system operates to formulate effective policies. The outcomes of this research are anticipated to contribute valuable insights that can inform policy decisions, infrastructure planning, and public awareness aimed at improving the cycling environment, reducing emissions and healthier mobility.

1.2 Literature review and research question

This subchapter presents a literature review from which a knowledge gap follows and then the research questions are introduced. The literature review begins with a brief overview of the history of e-bikes and their substitution effect in an international context. Then, it narrows its focus to studies examining the substitution effect specifically within the Netherlands. Finally, before identifying the research gap, the review explains the role of attitudes in relation to the substitution effect.

With the rising popularity of e-bikes, there is a growing assortment of research exploring the substitution effects. China is one of the countries where the e-bike was adopted first (C. R. Cherry et al., 2009). In the late 1990s and early 2000s, there was a large spike of sold e-bikes and the use of this transportation mode. One of the reasons for the large increase was the fact that several major Chinese cities banned the sale of gasoline-powered scooters (Weinert et al., 2007a). Besides that, multiple studies suggest that the e-bike could serve as a viable alternative to public transport (Cherry & Cervero, 2007; Montgomery, 2010). This trend emerged because people felt under-served by public transport, and the authors suggests that the e-bike is to some degree replacing the use of conventional bicycles (Weinert et al., 2007b).

When looking to other countries, mostly western countries, there are other findings which differ from each other. In a city in Poland a survey was conducted about e-bike sharing services and it concluded that the e-bike service acts as a substitute for public transportation and for first mile/last mile transport (Bieliński et al., 2021). This aligns with the observed trend in China. However, in Sweden, a controlled trial using GPS data was conducted, revealing a 25% increase in overall cycling. Remarkably, this increase came entirely at the expense of car usage (Söderberg f.k.a. Andersson et al., 2021). In North America, multiple studies indicate that the purchase of an e-bike resulted in less car use, suggesting that the e-bike replaces car trips (Johnson et al., 2023; MacArthur et al., 2014; Popovich et al., 2014).

Another study in Sweden also found that the car is primarily replaced by the e-bike, but this study also suggests that in urban areas more people replace their conventional bike by the e-bike compared to the rural areas (Winslott Hiselius & Svensson, 2017). Like Hiselius & Svensson (2017), there are more studies that align with the conclusion that the e-bike replaces not only the car but the conventional bike as well. A Danish study shows mainly the e-bike mainly replaces the conventional bike, but also the car (Haustein & Møller, 2016). Another study, among English and Dutch e-bike owners, tells the same narrative, namely that the use of the conventional bike and car were both reduced (Jones et al., 2016). Finally, a literature review study, concluded as well that the e-bike largely substitutes the conventional bike or private car trips (Bourne et al., 2020).

Overall, so far it can be concluded that the substitution effect of e-bikes differs from public transport to car to conventional bicycle. The substitution effect depends on multiple factors like type of country, mobility culture and available alternative travel modes. In China, it was observed that the e-bike replaced the public transport (Cherry et al., 2009; Weinert et al., 2007, Weinert et al., 2007). In countries which are car-orientated, mainly car trips were replaced by e-bikes (Johnson et al., 2023; MacArthur et al., 2014; Popovich et al., 2014; Söderberg f.k.a. Andersson et al., 2021). Whereas countries which are bicycle-orientated, the e-bike seems to substitute the conventional bike, next to the car (Haustein & Møller, 2016; Jones et al., 2016; Winslott Hiselius & Svensson, 2017).

When one focuses on the Netherlands, it looks like the e-bike ownership significantly reduces the use of the conventional bike and in lesser extent car use and public transport use (Kroesen, 2017). This fact aligns with the findings from the last paragraph, since the Netherlands is one of the largest bicycle countries in the world. Kroesen (2017) concluded: "on the level of vehicle ownership, the e-bike acts as a substitute for the conventional bicycle and does not act as a substitute for the car". However, car owners are more willing to use the e-bike as an alternative for car trips in contrast to conventional cyclers. This last statement aligns with the findings of de Kruijf et al. (2018) who researched a program that incentivised e-bike use. However, they found that the e-bike substituted 50% the car trips and 50% conventional bike trips. Additionally, they discovered that people are more likely to switch to e-bikes if they are dissatisfied with car commuting. Indeed, another study which monitored a small group of e-bike users, concluded that individuals commuting between work and home can effectively replace motorized modes of transportation with e-bikes (Plazier et al., 2017a). The same authors also did a study focused on e-bike adoption of students and the results show high potential for e-bikes to substitute public transportation use, but the high purchasing price makes it difficult for the e-bike to compete (Plazier et al., 2017b). In fact, larger research has shown that price is the main reason people did not or have hesitated about purchasing an e-bike (De Haas & Huang, 2022). Although the research from Plazier et al. (2017b, 2017a) show a great potential for replacing car use and public transportation by e-bikes, the current data shows that the e-bike mainly replaces the conventional bike.

Previous studies often assume that the substitution effects of e-bikes are homogeneous across the population. However, it is possible that some individuals primarily use e-bikes to replace car trips, while others mainly substitute them for bicycle trips. To assess the variation in substitution effects among different groups, this study considers the role of attitudes. Attitudes towards travel modes, such as cars, can impact an individual's decision to switch from one mode of transportation to another. (De Vos et al., 2022). The assumption is that individuals with pro-car attitudes are more likely to use e-bikes as a substitute for bicycles, whereas those with anti-car attitudes tend to use e-bikes to replace car trips. Research has consistently shown that attitudes are strong predictors of travel mode choice, often surpassing factors such as the built environment and residential location in their influence (Bagley & Mokhtarian, 2002; Kitamura et al., 1997). Additionally, significant effects of travel behaviour on travel attitudes have been identified, indicating a bidirectional relationship between the two (Kroesen et al., 2017).

Moreover, mode-specific attitudes not only influence travel mode choices but also impact satisfaction with trips. Studies suggest that satisfaction is not solely determined by the travel mode itself but also by whether an individual's attitudes toward that mode are positive (De Vos et al., 2022; Ye & Titheridge, 2017). Research shows that current and potential e-bike users tend to have more favourable attitudes toward various aspects of e-bike travel compared to non-users (Plazier et al., 2023). Additionally, those who value the fun aspect of e-bikes or hold a positive image of e-bikes are more likely to increase their e-bike use. Furthermore, positive attitudes toward walking and cycling are strongly associated with higher usage of active transport modes, which in turn discourages the use of cars (Arroyo et al., 2020).

In this complex interplay, it can be observed that attitudes play a crucial role in shaping travel behaviour. It has also shown that travel behaviour is influenced by the substitution effect of e-bikes replacing the conventional bike and car, with ownership of these modes being a significant factor. However, the specific impact of attitudes on this substitution effect of e-bikes has not been thoroughly explored. Previous studies on the substitution effect have largely treated the population as homogeneous, overlooking potential variations. Attitudes, however, can reveal heterogeneity within the population, leading to diverse travel behaviours based on individuals' perspectives toward different modes of transport.

Furthermore, studies examined how e-bike use affects the use of other modes of transport and vice versa over time (e.g. De Haas et al., 2021). Others examined the effect of e-bike ownership on use of travel modes in one year (e.g. Kroesen, 2017). However, these papers do not provide a temporal comparison of the effect of e-bike ownership (i.e. purchasing) on the use of other travel modes.

The main aim of this research is to investigate how attitudes influence the substitution effect of e-bikes on other modes of transport, highlighting the heterogeneity in travel behaviour. Additionally, this research provides a temporal comparison of the effect of e-bike ownership (i.e. purchasing) on the use of other travel modes. Furthermore, as the e-bike trends changes fast, it is useful to update the earlier research that investigated the substitutions effect. This new points of view could add value to literature to better understand the substitution effect of e-bikes. Such insights can inform policy decisions in the Netherlands, aiding policymakers in promoting e-bike adoption as a means to replace polluting transportation modes and mitigate emissions.

Based on the objectives of this research, three research questions have been formulated:

- To what extent do bike, e-bike and car ownership influence the use of different modes, controlling for social demographic characteristics?
- To what extent does the purchase of the e-bike influence the use of different travel modes over time?
- To what extent does the attitude towards the car moderate the relationship between e-bike ownership and the use of different modes?

The first question looks at the influence of e-bike ownership on use of transport modes with data from a given year. The second question involves the time aspect and analyses whether e-bike ownership change affects the use of transport modes over years. The third question involves the aspect attitude to the equation to research what the role of car attitude is with respect to travel behaviour and vehicle ownership

1.3 Method motivation

To address the research question, a quantitative approach will be employed. A quantitative approach allows researchers to quantify the effectiveness of measures, search for patterns in data, and assess hard data to understand behaviour. This research uses data of the Mobility Panel of the Netherlands (MPN) in order to analyse the data. With the Mobility Panel of the Netherlands (MPN), the KiM (Knowledge Institute for Mobility Policy) collects data on the travel behaviour of a fixed group of people and their households over several years (KiM, 2022).

This research will use two methods to answer the research questions: a cross-sectional regression model and the Difference-in-Differences (DID) method. The following sections provide a rationale for the selection of these methods.

Cross-sectional regression

Cross-sectional regression is a statistical method used to analyse the relationship between two or more variables within a single point in time. In this context of this research, the relationship between vehicle ownership, social demographics and the use of travel modes will be analysed.

There are several compelling reasons to choose for cross-sectional regression analysis in this research. Firstly, it can be valuable for policy analysis and decision-making, as it provides insights into the current state of affairs and the factors influencing it. Secondly, it is a simple and often straightforward method making it pleasantly interpretable. Lastly, it is an efficient method as they are less time consuming than longitude methods.

There are also disadvantages or downsides of the method that must be taken into account. First, cross-sectional regression assumes a linear relationship between the dependent and independent variables, which might not always hold true. Secondly, the accuracy of cross-sectional regression depends on the correct specification of the model, including the selection of appropriate independent variables. Thirdly, the presence of endogeneity or multicollinearity among the independent variables can lead to biased and unreliable estimates. Lastly, since cross-sectional regression analyses data at a single point in time, it provides limited insights into temporal changes and trends.

Difference-in-Differences

The second method that will be applied is called difference-in-differences (DID). With DID a researcher studies the effect of a treatment/policy on two groups, the control group and the treatment group (Schwerdt & Woessmann, 2020). It quantifies the impact of a treatment on an outcome by comparing the average change observed over a period of me. With DID the data of both groups before the treatment and at the data after the treatment are analysed. In this research, there will not be a policy or standard treatment observed. Instead, the event of travellers purchasing an e-bike will be considered as the "treatment" to be observed. In other words, the quantitative impact of purchasing an e-bike on the use of other travel modes will be compared.

There are several compelling reasons to choose for DID in this research. DID helps identify the causal impact of a treatment or intervention, while controlling for time-invariant confounders. DID controls for me-invariant confounders that affect both the treatment and control groups, eliminating potential biases associated with unobserved heterogeneity. DID results are often straightforward and easy to interpret, making them accessible to policymakers, stakeholders, and the public.

There are also disadvantages or downsides of the method that must be taken into account. DID considers the parallel trend assumption. This assumption relies on the hypothesis that, in the absence of treatment, the treated and control groups would have followed the same trend over time. Furthermore, there is the Stable Unit Treatment Value Assumption (SUTVA) which ensures that only two potential outcomes exist and that one of them is observed for each individual (Laffers & Mellace, 2020). Important aspects are that the composition of intervention and comparison groups are stable in repeated cross-sectional designs to avoid spillover effects. Additionally, exchangeability cannot be assumed between the treatment and control groups.

The two methods can really complement each other well. Before implementing the DID analysis, a cross-sectional regression can be used to understand the baseline relationship between the variables of interest. After establishing the baseline relationships, you can apply the DID method to estimate the causal effect, thereby it tackles the drawback of cross-sectional analysis by including the longitudinal aspect. Also, if certain social demographics (like age, education, or income) are found to affect the outcome in the cross-sectional analysis, including these variables in the DID model can help in obtaining more precise estimates.

Structure of thesis

This thesis is structured in the following manner: Chapter 2 proceeds with the conceptualisation concerning a conceptual model and the expected relationships. Moving forward, chapter 3 presents the methodology and discusses the data. Chapter 4 present the results and a discussion and in chapter 5 will follow a conclusion including limitations, recommendations and future research.

2. Conceptualisation

In this chapter will provide a conceptual framework for this research. Firstly, a context of the e-bike will be provided. A general introduction of the e-bike as a technology is given first, then current policies and regulations are discussed and finally the speed of adaption of the e-bike is shown. Secondly, the substitution effect will be examined in a more conceptual way, meaning researching what models and methods were used in earlier research. Thirdly, there will investigate what the determinants are for buying an e-bike. Also, the different kind of users with different kind of motivations will be portrayed. Lastly, conceptual models are presented for this research. A conceptual model is created to show the variables that are considered and what relationships are known/expected.

2.1 Context of the e-bike

An e-bike, or electric bicycle, is a bicycle equipped with an integrated electric motor that assists with propulsion. E-bikes have gained significant popularity due to their ability to combine the convenience of powered transport with the health benefits and eco-friendliness of traditional cycling. There is a large heterogeneity in types of e-bikes and the corresponding characteristics. The "e" in e-bike refers to a compact electric motor designed to assist the rider's pedalling efforts (SWOV, 2022). The types vary in speed, size, compliance with regulations etc. This is based on technical specifications like the engine used, battery and the type of gears. There are a lot of types that can be distinguished, but one can in any case distinguish two types, namely speed pedelecs and e-bikes (ANWB, n.d.; SWOV, 2022). Speed pedelecs are allowed faster than normal e-bike namely 45 km per hour. There is much more regulation for these bikes such as helmet requirement, rear view mirror and minimum age (Ministerie van Algemene Zaken, 2023). However, some people boost their e-bike so they can reach speeds higher than 45 km/h. The maximum speed of an e-bike is normally 25 km/h. There are a lot of variations on e-bikes which fall under this category. There are compact e-bike which are particularly small and compact, so storage and transportation are more convenient. There are many others like mountain bike, race bike, folding bike, cargo bike etc. There are also for example fat bikes which stand out because of their appearance and their attention in the news the last year.

The adoption of e-bikes in the Netherlands has seen a remarkable increase over the past decades. E-bikes began to gain traction in the early 2000s, with initial users primarily consisting of older adults. The focus was on providing a sustainable and manageable way for seniors to stay active and mobile. In the period of 2010 – 2015 was a growth phase with a significant rise in e-bike popularity, spurred by technological advancements, decreasing costs, and increasing environmental awareness. More urban commuters started to see e-bikes as a viable alternative to cars and public transport. In the last years, the e-bike market in the Netherlands has matured, with a wide range of models available to suit different needs. The COVID-19 pandemic further accelerated e-bike sales, as people sought safe, socially distanced modes of transport. By 2020, e-bikes accounted for over half of all new bicycle sales in the Netherlands.

The total number of bikes sold had remained stable at around 1 million units for a long time (RAI vereniging, 2023). However, since 2020, this figure has been gradually declining, while e-bike sales have also levelled off. According to the data, sales of new two-wheelers reached 804,000 units in 2024, compared to 855,000 units in 2022. Electric bikes accounted for over 56 percent of the market, totalling 453,000 units. Until 2020, e-bike sales saw rapid growth, but this trend has since slowed. The average price of bikes has been rising for some time, though this increase now appears to be stabilizing.

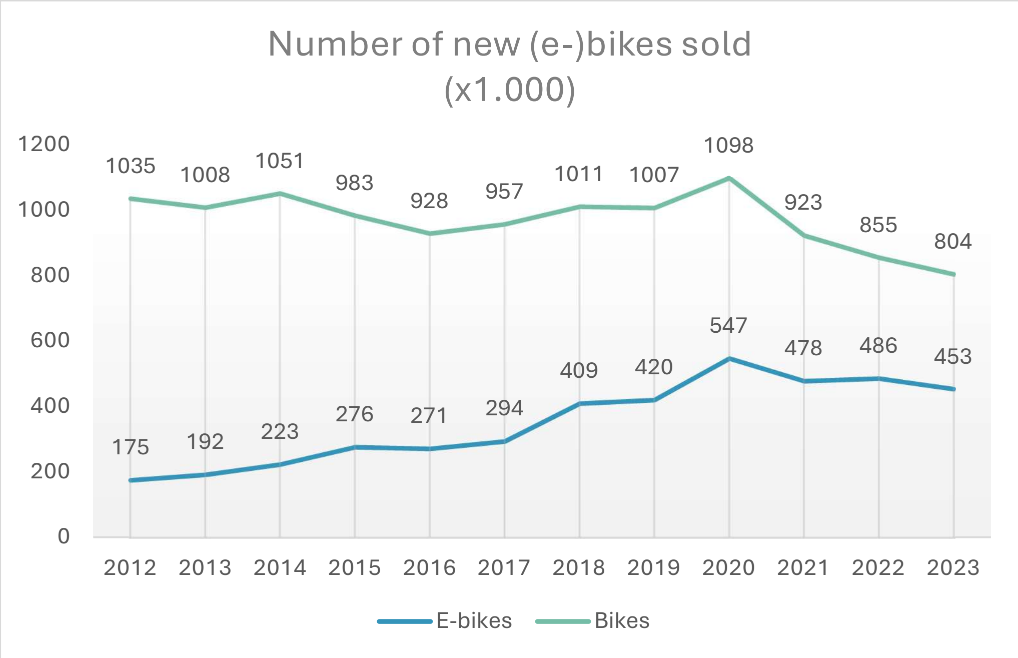

Figure 1: Total number of new sold (e-)bikes (RAI vereniging, 2023)

Policies and regulations are aimed to improve the road and traffic safety. For example, helmet obligation for all e-bikes, age restriction, driving licence obligation. An interesting case to study is the helmet requirement for mopeds since 1 January 2023 (Ministerie van Infrastructuur en Waterstaat, 2023). The consequence of that law made many people less keen to use the moped so many people switched to the e-bike. Van Schagen (2023) says achieving a tipping point appears crucial, wherein a substantial majority of cyclists embrace helmet usage, transforming the norm into wearing one and so not wearing one is the exception rather than wearing one, a departure from the current situation.

2.2 Users, motivations and determines for purchase

This subsection will explore various types of e-bike users, their motivations for purchasing e-bikes, and additional factors influencing their decision-making process. As this study tries to investigate the heterogeneity within the population, it is important to put things in perspective. So, context around different kind of users is relevant as well as why the different users want to buy an e-bike. This approach enhances the understanding of the results by building on the existing knowledge of heterogeneity.

Studies have already been conducted on the relationship between social demographics, vehicle ownership and travel behaviour. Kroesen & Harms (2018) noticed that the middle-aged and younger demographics utilizing e-bikes for practical purposes are significantly growing in prominence within the Netherlands. Let's put this into perspective and zoom in on the specific groups that are utilizing e-bikes extensively. When focusing on those different users, De Haas (2019) identified five different user groups:

1. Retired older leisure users
2. Full-time working middle-aged people
3. Older female leisure users

4. Younger part-time working women with children
5. Pupils/students

It is pretty clear by the aforementioned research and news articles that older people were the early adopters of the e-bike. The first and third user groups both consist of relatively old people (65+ and 50-65 years) who use the e-bike mainly for leisure purposes. However, a shift in users is visible. The proportion of older people (over-65s) is decreasing, and e-bikes are used more often for work-related/education-related travel. Especially in groups 2, 4, 5 is this the case. Analysis of longitudinal data reveals that, across all trips, e-bike trips primarily substitute only the conventional bicycle (De Haas et al., 2021). However, across only commuting trips, the e-bike appears to substitute the car in addition to the conventional bicycle and this commuting group is apparently increasing. Furthermore, Sun et al. (2020) found that e-bikers in rural areas tend to be more likely to reduce their car use.

The motivation for this rising commuting group (education also included) to purchase an e-bike is also more focused on faster speeds and being able to travel longer distances (De Haas & Huang, 2022; Van Deemter et al., 2022). This compared to largest motivation for e-bike purchase in general which is ease, convenience and comfort (still is) which primarily applies to elderly people who were the early adopters of the e-bike. These two motivations (speed and convenience) seem like reasons to substitute the conventional bike. The trip motives also influence the adoption of an e-bike as the acceptable distance for commuting and education are 9,5 km and those of shopping are shorter but for leisure are longer (De Haas, 2023). There are also motivations for purchasing an e-bike which are more related to car substitution, like environmental reasons and cost. E-bikes pollute significantly less CO2 than a car, which could be a reason for people who consider this important and are willing to change their travel behaviour. An e-bike could lower the transport costs as cars need gas, insurance and taxes which could be significant depending on the car. Interestingly, the most important barrier to buy an e-bike is the price. The price of an e-bike compared to a conventional bike is in fact relatively large. Battery life and perceived health are also known barriers of buying an e-bike.

Perceived health is also an important reason but also a contradicting reason because that is at the same time also a reason for people not to buy an e-bike, but it depends on what their current mode of travel is. If individuals are currently using a conventional bike, switching to an e-bike may result in less exercise, potentially impacting their health negatively. Conversely, if individuals primarily rely on cars for transportation, transitioning to an e-bike would likely increase physical activity levels, positively impacting their health. Nonetheless, health is an interesting aspect that is currently under study because it is more nuanced than simply switching modes of transportation, as more factors such as trip frequency and duration of trips also play a crucial role in influencing overall health. However, this is not really in scope of this research.

2.3 Substitution from a method perspective

With the rising popularity of e-bikes, a growing body of research is exploring their substitution effects on other modes of transport. This section reviews the methodologies used in previous studies to understand these effects, focusing on various countries and contexts.

Researchers Weinert, Ma, & Cherry (2007); Weinert, Ma, Yang, et al. (2007) conducted surveys to assess the impact of this policy change, finding that e-bikes served as a viable alternative to public transport and, to some extent, replaced conventional bicycles. Similarly, Cherry & Cervero (2007) and Montgomery (2010) used surveys and questionnaires with the help of a regression analysis, to explore the potential of e-bikes to fill gaps in underserved public transport systems.

In Poland, Bieliński et al. (2021) conducted a survey on e-bike sharing services, concluding that these services acted as substitutes for public transportation and first mile/last mile transport, mirroring trends observed in China. Meanwhile, in Sweden, a controlled trial using GPS data by Söderberg f.k.a. Andersson et al. (2021) revealed a 25% increase in overall cycling, entirely at the expense of car usage. GPS tracking data analysis and time-series analysis to observe changes in travel patterns over time, and paired t-tests to compare pre- and post-trial cycling and car usage data.

In North America, multiple studies utilised surveys to measure the impact of e-bike purchases on car usage. Johnson et al. (2023), MacArthur et al. (2014) and Popovich et al. (2014) found that e-bike ownership led to a reduction in car trips. They used chi-square tests to assess the relationship between e-bike ownership and reduced car use, and logistic regression to predict the likelihood of reduced car usage based on e-bike ownership. In Denmark, Haustein & Møller (2016) used surveys to show that e-bikes primarily replaced conventional bikes, but also cars. Similarly, Jones et al. (2016) conducted surveys among English and Dutch e-bike owners, finding reductions in both conventional bike and car use by using multivariate regression analysis.

Bourne et al. (2020) performed a literature review to summarise the substitution effects of e-bikes, concluding that e-bikes largely replace conventional bike and private car trips. This aligns with findings from other countries, highlighting the variability in substitution effects based on local context.

In the Netherlands, Kroesen (2017) used cross-sectional data to analyse the impact of e-bike ownership, concluding that e-bikes mainly substitute conventional bicycles and have a lesser effect on car and public transport use. De Haas et al. (2021) employed longitudinal data to examine the yearly effects of e-bike usage on other modes of transport, shedding light on how e-bike use evolves over time and interacts with other travel modes. Additionally, de Kruijf et al. (2018) analysed an incentive program designed to promote e-bike use, finding that e-bikes substituted 50% of car trips and 50% of conventional bike trips. This was done by paired t-tests to compare travel behaviour before and after program implementation. P. A. Plazier et al. (2017a) and P. A. Plazier et al. (2017b) conducted studies on e-bike adoption among commuters and students, using surveys and monitoring to determine the potential for e-bikes to replace motorized and public transport. Finally, market research and conjoint analysis by De Haas & Huang (2022) identified the high purchasing price as a significant barrier to e-bike adoption, influencing their substitution potential.

Overall, the research reviewed here highlights the diverse methodologies used to study e-bike substitution effects, including surveys, controlled trials with GPS data, longitudinal studies, and market research. These studies collectively show that the substitution effect of e-bikes varies depending on the country, mobility culture, and available alternative travel modes.

2.4 Conceptual models

This subchapter presents the conceptual models which visually show the relationships between the variables. Each model aligns with a research question which means that a model treats a certain part of the research question. Every model will be discussed below with explanation of the chosen variables and the proposed relations.

Below in Figure 2, the conceptual model illustrates the variables socio-demographics (SD), vehicle ownership and travel behaviour, for the cross-sectional regression. This model aligns with the first research question. Now, let's discuss the model element by element. Firstly, the social demographics function as control variables. Controlling for socio-demographic variables allows this research in some extent to isolate the true effect of e-bike ownership on travel behaviour (Thomas, 2020). Thereby, including the socio-demographic variables can strengthen the validity of the research by limiting the confounding variables.

Now, let's examine which socio-demographic factors are included in the model and why they are included. The first variable is gender. Research has consistently shown differences in travel behaviour between men and women. For instance, De Haas (2019) found that women account for about two-thirds of e-bike trips, making gender a relevant factor for this study.

Next is age, which intuitively influences travel behaviour because age defines your stage of life and that also shapes your needs in travel. Younger individuals tend to prefer more active modes of transport, such as walking or cycling, while older adults often rely more on cars or public transport. Additionally, previous research has shown that older people were early adopters of e-bikes, indicating that age is a key variable to consider (De Haas, 2019). Education level is another important factor. For example, people with higher education levels travel more by car to work both in terms of time and distance. Studies also indicate that people with a higher education level are more likely to own a conventional bicycle and less likely to own an e-bike than less educated people (Dingil & Esztergár-Kiss, 2021; Kroesen, 2017). Household income, closely related to education level, also plays a role. Higher-income individuals typically have more resources, allowing them to choose more expensive travel options like cars or trains. Research shows that higher-income people are more likely to purchase an e-bike than low-income people (De Haas & Huang, 2022; Kim et al., 2023). Work situation is another crucial variable, as it strongly influences travel patterns. Working individuals often commute to work, students travel to school, and pensioners travel a lot for leisure. The large group of e-bike owners are pensioners, and they will have different travel patterns with respect to locations and time, than the other groups. These differing patterns justify the inclusion of work situation in the model. Licence ownership is the next considered variable. Evidentially, having a driver's license naturally increases the likelihood of car usage and ownership, making it an important factor in understanding travel behaviour. The level of urbanity or residential location is another key factor. Traveling while living in the city is a different experience than in a rural area. Public transport is often more accessible in urban areas than in rural areas. Due to the lower population density in rural regions, residents are more reliant on cars, particularly because of the longer distances they need to travel. The e-bike might offer a car alternative in rural areas, making urbanity a relevant variable to investigate. The last socio-demographic variable is household size. Larger households, particularly those with children, may prefer cars for more efficient travel. Additionally, larger households may share vehicle ownership among members of the household. Similarly, research suggests that household size correlates with an increase in the number of trips (Tillema & Jorritsma, 2016).

Vehicle ownership is the next key variable in the conceptual model shown in Figure 2. While the primary focus is on e-bike ownership, it's not only important to understand how often people use their e-bikes but also whether this reduces car usage. Given the interdependence of travel modes, it is crucial to include car and conventional bike ownership to assess their influence on travel behaviour. Previous research indicates that e-bikes can replace both conventional bikes and cars, making it essential to examine the role of vehicle ownership in this dynamic (Kroesen, 2017).

The final variable in the conceptual model is travel behaviour. This research will explore the use of various travel modes, including e-bikes, conventional bikes, and cars, as highlighted in the ownership section. Public transport use is also included as a potential alternative to both bikes and cars.

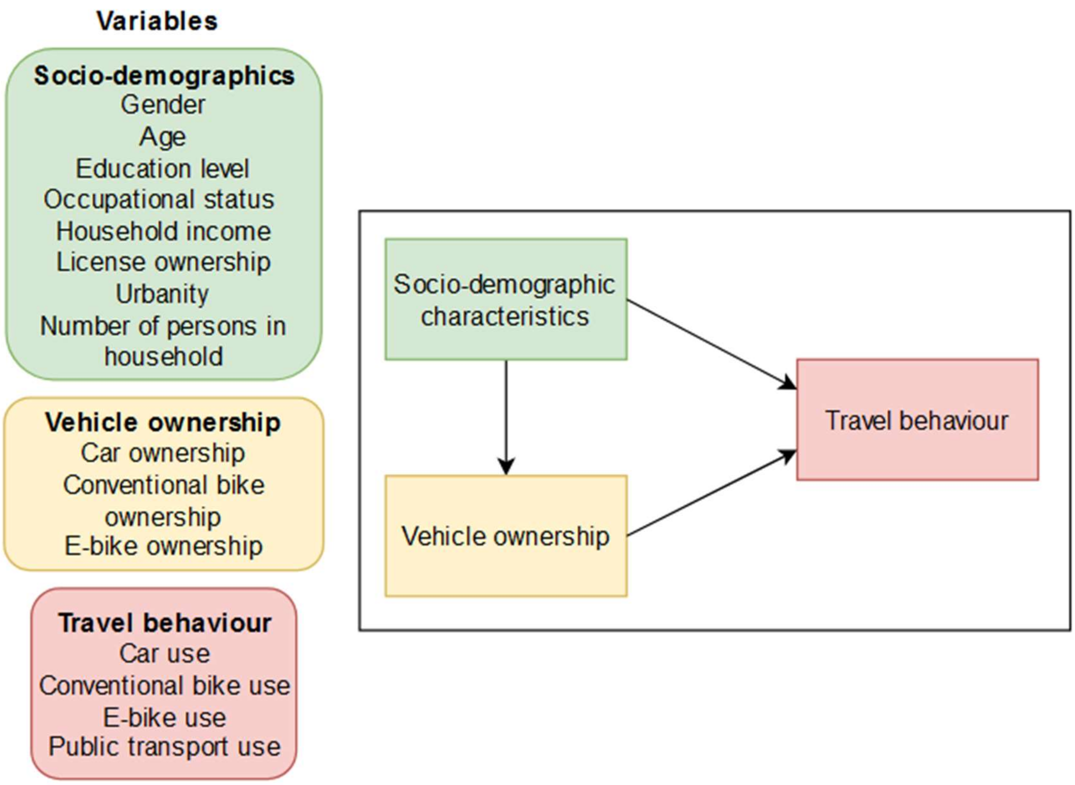

Figure 2: Conceptual model regression

Then in Figure 3, the conceptual model including the attitudes is presented. It is an extension of the conceptual model in Figure 2. This model is the framework for the third research question whether attitudes have an influence on vehicle ownership and travel behaviour. Attitudes toward cars are chosen for this study because the purpose of the study is to encourage this group to switch to e-bikes. People's perceptions, preferences, and emotional connections to cars can affect how often they use them, and whether they are open to using alternatives like e-bikes or public transport. For example, those with a positive attitude toward cars may prefer driving due to comfort, convenience, or status, and may be less likely to adopt e-bikes or other modes of transport. Conversely, individuals with negative attitudes towards cars, perhaps due to concerns about environmental impact, cost, or traffic, might be more inclined to use e-bikes or public transportation.

From this attitude variable, two effects emerge. First, car attitude directly influences the use of travel modes. The second effect is a moderating effect on the relationship between vehicle ownership and travel behaviour. This means that car attitude functions as a moderator, influencing both the strength and direction of the relationship (King et al., 2013). The car attitude can either strengthen or weaken the relationship between vehicle ownership and mode use. The expected effect on travel behaviour is that individuals with a strong preference for cars may demonstrate less willingness to use other modes, even if they own an e-bike, whereas those with a neutral or negative attitude towards cars are more likely to substitute car trips with e-bike or other transport modes.

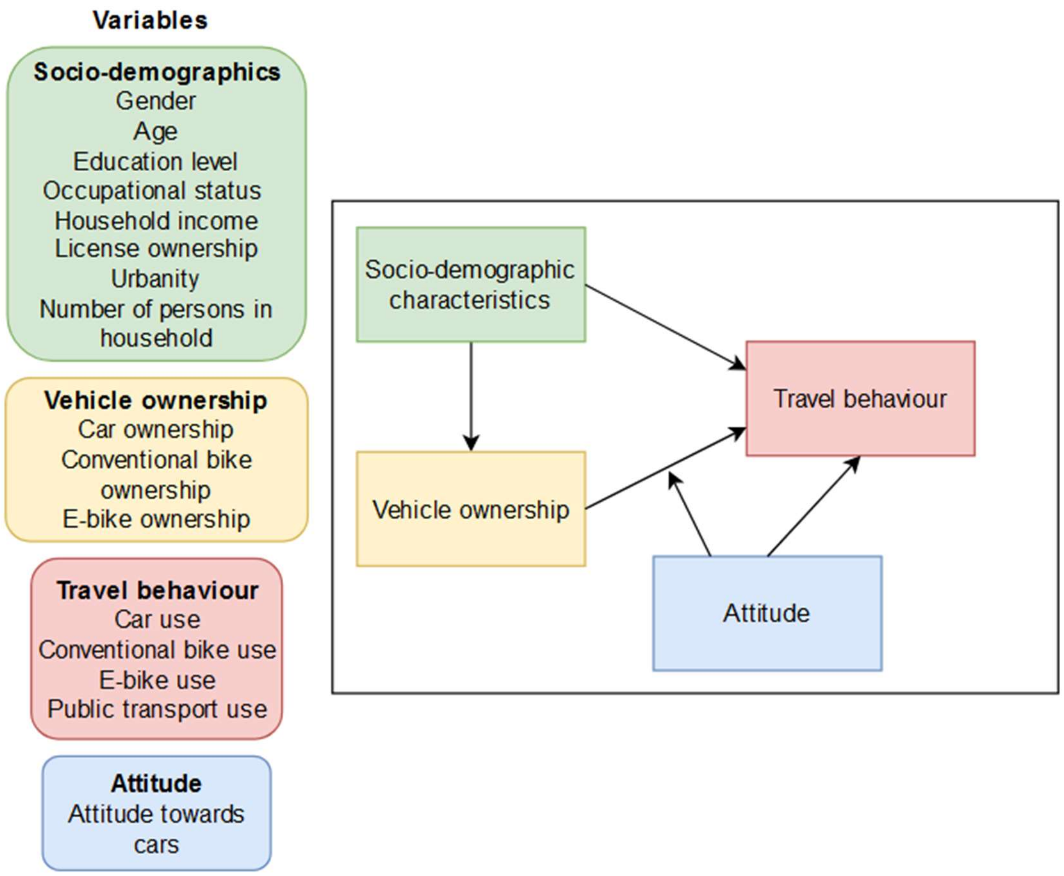

Figure 3: Conceptual model including attitudes

DID

Below in Figure 4, the conceptual model illustrates the application of the Difference-in-Differences (DID) method. This model aligns with the second research question which incorporates the temporal factor, in order to assess how ownership and mode use have evolved over time. It shows the same variables on both the left and right side, representing the variables during year 1 (T1) and year 2 (T2) respectively. The triangles indicate the differences in variables between two time points (T1 and T2). So, in other words, the difference in e-bike ownership between two years will have an influence on the difference in use of travel modes between those same two years. Intuitively, one would expect that people who do not have an e-bike one year and do the following year, would use the e-bike more, ergo a positive correlation. It will be interesting to investigate if the purchase has any effect on other travel behaviour.

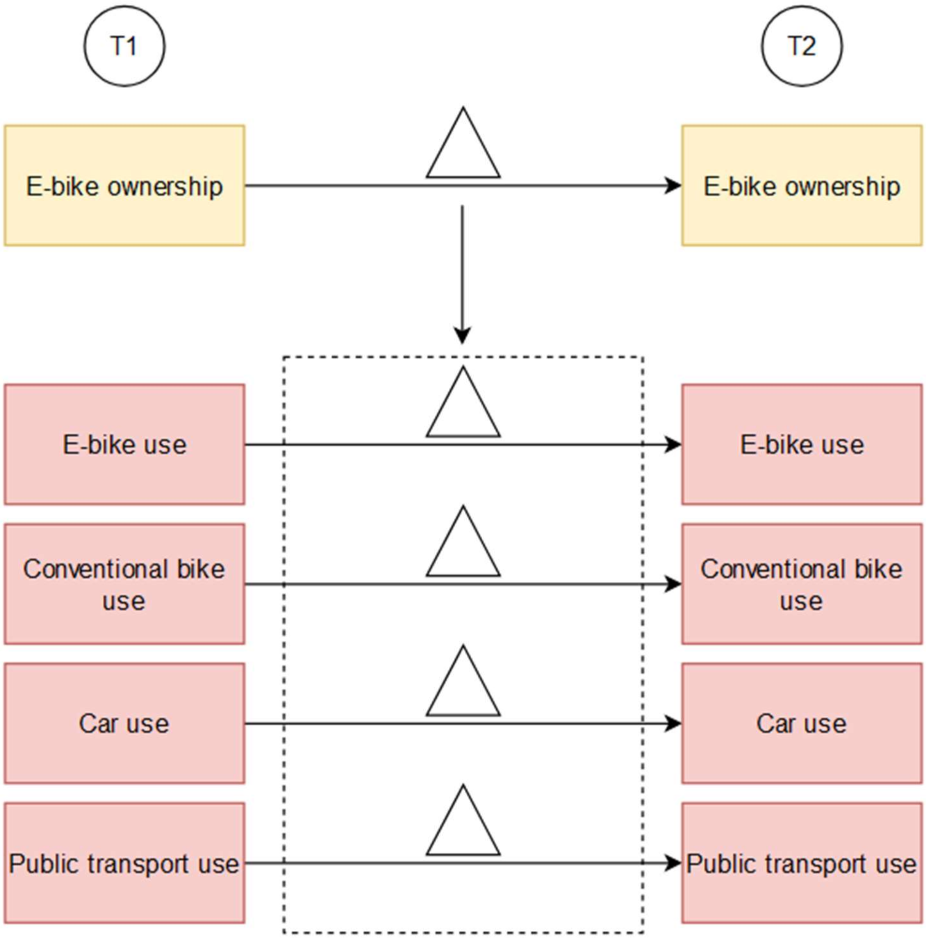

Figure 4: Difference-in-Differences (DID)

3. Method

The primary objective of this research is to investigate the relationship between travel behaviour and several independent variables, including vehicle ownership and attitudes. To achieve this, a multiple linear regression model is employed, which allows to quantify the effect of each independent variable on the outcome while controlling for social demographics. In 2.4 was an explanation of which socio-demographics and other variables are considered for this research.

Multiple linear regression is used to analyse the relationships between multiple variables across multiple observations at a certain point in time (Müller, 2023). It serves as a powerful analysis for researchers across various disciplines, enabling them to explore the interdependencies among different factors and understand the dynamics of complex systems (Maier et al., 2023). By examining data collected from different individuals at a single instance, multiple linear regression offers valuable insights into how various factors influence outcomes or behaviours of interest.

In the model, each coefficient represents the expected change in the dependent variable for a one-unit change in the corresponding independent variable, holding all other variables constant. This chapter will show that this research considers continuous variables and dummy variables.

Subchapter 3.1 will present the dataset used for the analysis and hoe that dataset looks like. 3.2 shows the descriptive data of the variables and reflects on the representativeness of the data. 3.3 present which models exactly will be estimated and how that will happen. There will be a description on what steps were taken to collect the results wanted.

3.1 Data

This research requires panel data in an aggregated cross-sectional or longitudinal format, requiring observations both before and after the purchase of an e-bike. Therefore, the Mobility Panel of the Netherlands (MPN) will be used in order to analyse the data. With the Mobility Panel of the Netherlands (MPN), the KiM (Knowledge Institute for Mobility Policy) collects data on the travel behaviour of a fixed group of people and their households over several years (Hoogendoorn-Lanser et al., 2015; KiM, 2022). The KiM is collects data since 2013 and the most recent data comes from 2021. Respondents (12 years and older) from about 2,000 complete households track their mobility behaviour in a travel diary for 3 days. In this diary, they record not only all their trips, but also the mode of travel, their travel companions, delays and parking costs. Furthermore, participants are requested to provide information regarding their personal and household characteristics. These are social demographics like gender, age, income etc.

The decision has been made to utilise data from 2018 and 2019, which represents a period unaffected by the pandemic and provides a more stable baseline for analysis. Ideally, the goal is to utilise the most recent available data, typically from 2021. However, due to the lingering effects of the COVID-19 pandemic during that year, including measures such as evening curfews, vaccination campaigns, and significant disruptions in travel behaviour, the data from 2021 may not accurately reflect the pre-pandemic conditions (Rijksoverheid, 2024). In the Netherlands, these pandemic-related factors heavily influenced societal norms, with remote work becoming prevalent and various restrictions in place.

So, the present study uses the data from 2018 and 2019. The number of participants for these year were respectively 8805 and 7226. After a selection of excluding not valid participation, the effective sample size for the analysis was respectively 6121 and 5351.

This study examines three categories of variables: vehicle ownership, vehicle use, car attitude and socio-demographic/household characteristics. Under vehicle ownership, data is collected for car ownership, conventional bike ownership, and e-bike ownership. Vehicle use is measured by two variables: total distance travelled and total number of trips over a three-day period. This research will use total distance travelled, because trips have the obvious disadvantage of not indicating the distance of the trip. The attitude toward cars is operationalised using six statements. Each statement measures a person's attitude toward cars. All the statements are phrased positively, meaning that a higher score indicates a more positive attitude toward cars. For more details, see Appendix D: Histogram indicators. Socio-demographic and household characteristics include gender, age, level of education, household income, occupational status, and license ownership.

As seen in subchapter 2.1, speed pedelecs are a specific kind of e-bike to consider in this research. However, they are not included as the group was too small in the dataset and this can lead to unstable estimates which are hard to generalise. Also, scooters/mopeds were not considered as that group was also small and the theory does not give a strong reason to suspect a significant role of scooters/mopeds regarding e-bikes in the Netherlands.

3.2 Descriptive statistics

Table 1 presents the descriptive statistics of the social demographics. There are several statistics that are noticeable when putting them alongside to representativity of the Netherlands and overall trends in demographics (Statistics Netherlands, n.d.-a). Overall, data is broadly representative of the Dutch population based on the general alignment with known demographic patterns. The demographic residential density data indicates that the proportion of people living in rural areas is lower than the actual figures, while the number of people in very urban areas is higher compared to known CBS statistics (Statistics Netherlands, n.d.-b). Also, the amount of people owning a licence is higher than other data suggests.

Table 1: Social demographics data

Variable			2018 N = 6123	2019 N = 5352	Population
Gender	Male	%	47	47	49.7
	Female	%	53	53	50.3
Age	12-24 year	%	15.2	13.7	19.9
	25-29 year	%	6.1	5.9	7.2
	30-39 year	%	16.4	15.5	13.6
	40-49 year	%	14.5	14.9	14.6
	50-59 year	%	18.2	17.8	16.2
	60-69 year	%	15.9	16.8	13.5
	70-79 year	%	11	12.2	9.8
	80 year and older	%	2.6	3.3	5.3
Level of Education	Practical	%	33	32	30
	Medium	%	37	37	40

	Theoretical	%	30	31	30
Primary occupation	Employed	%	51	51	52
	Student/pupil	%	13	11	12
	Retired	%	19	21	18
	Other	%	17	17	18
Licence ownership	Yes	%	85	85	80
	No	%	15	15	20
Household income	Minimum (< € 14.100 Euro)	%	5.9	4.4	4.4
	Below modal (€ 14.100 - < € 29.500)	%	20	20.4	28.5
	Modal (€ 29.500 - < € 43.500)	%	22.9	24	36.5
	1-2x Modal (€ 43.500 - < € 73.000)	%	25.5	25.4	19.7
	2x Modal (€ 73.000 - < € 87.100)	%	5.3	5.1	6.8
	More than 2x modal (>= € 87.100)	%	7	7.2	5.1
	Don't know / Don't want to say	%	13.5	13.4	
Residential density	Strongly urban	%	24.2	23.4	24.6
	Very urban	%	31.2	31.3	24.9
	Moderate urban	%	17.2	17.9	16.9
	Slightly urban	%	20.1	20	16.8
	Not urban	%	7.4	7.4	16.8
Number of household members	Mean	#	2.06	2.01	2.11

Table 2 presents the descriptive statistics of the vehicle ownership. As suspected, there is a large increase in e-bike ownership from 20% in 2018 to 25% in 2019 (De Haas & Huang, 2022; Multiscope, 2024). This is consistent with the data known about progress of e-bike ownership. It is known that the COVID-19 pandemic caused a significant surge in e-bike sales, resulting in 35% of people owning an e-bike by 2020, while in 2015 it was 13%. Besides that, the percentage of conventional bike and car ownership are relatively constant. Although, the percentage of conventional bike and car ownership in the dataset are both a little lower in comparison to the population.

Table 2: Vehicle ownership

Vehicle ownership			2018 N = 6123	2019 N = 5352	Population 2019
Conventional bike	Yes	%	67	65	70
	No	%	33	35	30
E-bike	Yes	%	20	25	25
	No	%	80	75	75
Car	Yes	%	70	72	74
	No	%	30	28	26

Table 3 presents the descriptive statistics of the distance travelled per travel mode. The numbers in table 3 are distances travelled over a period of three days. This means that, for example, the average Dutch person travelled 5.7 kilometres (km) on a conventional bike over a span of three days in 2018. Additionally, the yearly mean for both e-bike owners and non-e-bike owners in the sample are presented. The use of the conventional has decreased from 5.7 km in 2018 to 4.5 km 2019. The e-bike use is the same over the 2 years and the distance travelled by the e-bike is lower than the conventional bike. E-bike owners use the e-bike much more than non-owners and use the conventional bike less than non-owners. Although, e-bike owners travelled their e-bike less in 2019 compared to 2018. The distance travelled by car and PT are much higher, however, that is of course reasonable taking into account the higher speed of the modes. The distance by car is pretty much the same in 2018 and 2019. The distance travelled by PT has reduced a little in 2019 compared to 2018. It is remarkable that e-bike owners travel less by car and PT than non e-bike owners. The total distance travelled in 2018 is slightly higher than in 2019, however, this could be explained by the larger number of observations recorded in 2018.

Table 3: Distance travelled per mode

Distance travelled			2018 N = 6008			2019 N = 5268		
			All	Owners	Non-owners	All	Owners	Non-owners
Conventional bike	Mean	Km	5.7	1.8	6.7	4.5	1.4	5.5
E-bike	Mean	Km	2.3	9.9	0.3	2.2	7.9	0.3
Car driver	Mean	Km	54.3	46.1	56.4	53.5	44.6	56.4
PT	Mean	Km	38.5	16.8	43.0	35.9	19.5	41.3
Total	Mean	Km	100.9			95.0		

3.3 Model estimation

The cross-sectional regression analysis is divided into four analyses, encompassing data from both 2018 and 2019. The first analysis examines ownership as the independent variable and mode of use as the dependent variable. The second analysis focuses on socio-demographic factors as independent variables and their influence on vehicle ownership. Since the dependent variable for vehicle ownership is binary (i.e., "Yes, I own vehicle X" or "No, I do not own vehicle X"), logistic regression was employed for this analysis. The third component investigate the relationship of vehicle ownership and mode use, but now controlling for socio-demographics.

The fourth analysis includes the attitude variable. Additionally, for the Difference-in-Differences (DID) analysis, a model is estimated using data from both 2018 and 2019. The statistical software SPSS was utilized to execute the analyses.

For the first research question, regression analyses were conducted for both 2018 and 2019. Given that the analysis for the third research question (regarding attitudes) was performed solely for 2018, because attitude is not available in the 2019 dataset. While 2019 data are included in the overall analysis, any similarities or differences between the two years will be highlighted in the results section. The second research question integrates data from both years, as necessitated by the DID (Difference-in-Differences) methodology.

In order to perform the analysis, the data is customised in the form so the results can be interpreted. Regarding the socio-demographics, dummy variables are made for the regression analysis. Appendix A: Dummy codes scheme shows the dummy code schemes. The ownership variables were already in the proper form for analysis. For distance travelled, since every respondent in the data had multiple observations, the distances are aggregated to an individual person in the dataset. Concerning the attitudes, a factor analysis is performed including the six statements:

- I find travelling by car comfortable
- I find travelling by car relaxing
- Travelling by car saves me time
- Travelling by car is safe
- I find travelling by car flexible
- Travelling by car is pleasant

Factor analysis

A factor analysis has been conducted to identify latent variables (factors) that explain the patterns of correlations among observed variables. In this case, the variables consist of statements about attitudes toward cars, including how people experience traveling by car and their perceptions of cars. In Appendix C: Factor analysis are the results presented. All indicators meet the specified lower limit of communality, set at 0,25. Based on the total variance explained, a single factor can be extracted. There is one factor with an eigenvalue greater than 1, indicating that it accounts for a significant amount of variance. All six indicators are explained by one factor. As seen in Table 4, all the factor loading are larger than 0,5, in fact all factor loading is larger than 0,7. This indicates that there is a strong correlation between the indicators and the factor.

Table 4: Factor matrix

Factor Matrix		
	Factor	**Mean**
I find travelling by car comfortable	0.841	4.32
I find travelling by car relaxing	0.788	3.80
Travelling by car saves me time	0.710	4.15
Travelling by car is safe	0.787	3.91

I find travelling by car flexible	0.786	4.31
Travelling by car is pleasant	0.864	4.01

After conducting a factor analysis, the next step was to determine whether multiple indicators could be combined into a single scale. This process involved generating a sum score for the set of indicators, in order to operationalise the attitude variable. To ensure that these indicators could be meaningfully aggregated, a reliability analysis was conducted using Cronbach's alpha, which evaluates the internal consistency of the items within the scale.

The Cronbach's alpha value obtained was 0.910, well above the commonly accepted threshold of 0.7 for acceptable reliability. A value higher than 0.9 indicates a very high degree of reliability, suggesting that the items measure the same underlying construct consistently. Based on this result, it was deemed appropriate to create a sum score by combining the individual indicators into a single composite variable.

Equations

To clearly illustrate the structure of the regression analysis, the corresponding formulas are presented. These formulas provide a mathematical representation of how the model functions and captures the relationships between variables.

The regression model is formulated as follows:

$$Use\ of\ mode_x = constant + \beta_n * X_n + \beta_n * D_n$$

$$Use\ of\ mode_x = constant + \beta_n * X_n + \beta_n * D_n + \beta_n * Attitude_{car} + \beta_n * (Attitude_{car} * P_{e-b})$$

$$Delta\ use\ mode\ X = constant + \beta_1 * P_{ebike}$$

Where:

- β_n: Regression coefficients for each independent variable including social demographics, vehicle ownership, attitude and interaction effect
- X_n: Independent variables including social demographics and vehicle ownership
- D_n: Dummy coded independent variables

4. Results and discussion

This chapter presents and discusses the findings of this research. Firstly, in subchapter 4.1, results will be presented by means tables and reporting text. In 4.2 the discussion puts the results in a broader context.

4.1 Results

The results are discussed based on and treated in order of the research questions. For each question, the relevant results are discussed, with tables presenting the standardized coefficients of the variables and their significance (p-value). Standardized coefficients allow for direct comparison of the relative importance of each independent variable in predicting the dependent variable. This is particularly useful when the independent variables are measured on different scales or units, as it puts all variables on the same scale. These values are interpreted to assess their impact on travel behaviour. Additional, more detailed results are provided in Appendix B: Results.

4.1.1 Influence of vehicle ownership on mode use

- To what extent do bike, e-bike and car ownership influence the use of different modes, controlling for social demographic characteristics?

This question will be answered by first looking at the influence of bike, e-bike and car ownership on the use of bike, e-bike, car and public transport (PT). Subsequently, the social demographics are added to see what the effect of those are. The results are shown in Table 5: Multiple regression analysis results below, with the standardised coefficients and the significance (p-value). The coefficients that are not statistically significant are highlighted in red. More detailed results are in B.2 Ownership on use and B.3 Ownership on use (controlling for SD. Those results, like unstandardised coefficients, will also be used in the analyses to get a better understanding. The unstandardized coefficients allow for the interpretation of the actual units of change in the dependent variable for a one-unit change in the independent variable, facilitating a clearer understanding of the magnitude and direction of these relationships in practical terms.

Firstly, a significant finding is that e-bike ownership is negatively correlated with bicycle usage. This indicates that e-bike substitutes conventional bike use. A second significant result is that e-bike ownership is negatively correlated with car use which suggests that e-bike ownership reduces car travel. Thirdly, e-bike ownership is highly correlated with e-bike use. This effect is so large that the un-standardised coefficient indicates that if a person owns an e-bike, that person will use the e-bike over 10 km more.

Next, other findings will be presented. Car ownership and bike ownership have no significant effect on e-bike use. Furthermore, bike ownership is positively correlated with bike use, which makes sense. Car ownership is also negatively correlated with bike use. Then regarding car use, car ownership significantly increases the car use itself. The coefficient of conventional bike ownership is insignificant, although the 2019 analysis shows a small positive effect on car use. Regarding PT use, car ownership is negatively correlated with PT use. So, that indicates that people who own a car will travel less with public transport. The e-bike ownership coefficient is not significant, so e-bike ownership has no effect on PT use. Conventional bike ownership is significant and correlates positive with PT use. This last effect could be explained in the context of multimodal travel. People who own conventional bikes may be more likely to combine different modes of transport, such as biking to a public transport station and then continuing their journey by bus or train.

Table 5: Multiple regression analysis results

Standardized Coefficients		Use per mode							
		E-bike use		Bike use		Car use		PT use	
		Beta	**P-value**	**Beta**	**P-value**	**Beta**	**P-value**	**Beta**	**P-value**
Car ownership		-0.02	0.07	-0.09	0.00	0.28	0.00	-0.15	0.00
E-bike ownership		0.36	0.00	-0.06	0.00	-0.06	0.00	-0.02	0.06
Conventional bike ownership		0.00	0.72	0.14	0.00	0.02	0.15	0.07	0.00
R-square		0.13		0.04		0.080		0.03	
Car ownership		-0.02	0.24	-0.05	0.02	0.18	0.00	-0.14	0.00
E-bike ownership		0.39	0.00	-0.06	0.00	-0.03	0.07	0.01	0.78
Conventional bike ownership		0.01	0.40	0.12	0.00	-0.02	0.25	0.05	0.01
Gender (reference = male)	Female	-0.01	0.55	-0.01	0.62	-0.11	0.00	-0.01	0.65
Age (reference = 12 - 29)	30 - 49	0.02	0.63	0.01	0.83	-0.04	0.28	-0.08	0.02
	50 +	0.03	0.36	0.02	0.69	-0.09	0.01	-0.11	0.00
License ownership		0.01	0.44	0.03	0.12	0.03	0.10	0.01	0.77
Primary occupation (reference = other)	Working	0.04	0.09	0.01	0.57	0.13	0.00	0.11	0.00
	Retired	0.04	0.09	0.05	0.07	0.01	0.70	0.07	0.00
	Student	0.01	0.63	0.04	0.04	-0.01	0.64	0.12	0.00
Education level (reference = low)	Medium	0.00	0.82	0.00	1.00	0.07	0.00	0.03	0.20
	High	0.00	0.93	0.07	0.01	0.11	0.00	0.08	0.00
Household income		-0.01	0.42	0.00	0.97	0.07	0.00	0.02	0.39
Urbanity (rural is higher)		0.00	0.89	-0.03	0.08	0.06	0.00	0.00	0.91
Number of persons in household		-0.01	0.74	-0.01	0.69	-0.05	0.00	-0.05	0.01
R-square		0.16		0.03		0.13		0.07	

The influence of ownership on the mode use is now, controlling for social demographic characteristics, quite similar, which means the direction of correlation and order of magnitude are more or less the same. However, there are two essential changes, and they appear both in car use. E-bike ownership was negative correlated with car use, however, that variable it is just not significant anymore. However, what makes it more complicated, e-bike ownership is still significant in the analysis of 2019. Overall, the effect remains somewhat ambiguous. Furthermore, the second change is that the coefficient of car ownership on car use is still positive but quite smaller. This indicates that social demographics account for much of the explanation of car use, reducing the direct impact of car ownership itself.

Now, the overall results of the analysis are considered, including social demographics. When examining e-bike use, e-bike ownership emerges as by far the strongest predictor. Interestingly, none of the other independent variables are significant. If e-bike ownership is the only significant independent variable, this could suggest that simply owning the e-bike is a strong determinant of whether people use it, more so than their social demographic characteristics.

Then analysing the use of the conventional bike. There is observed that bike ownership is a strong predictor of bike use, and that e-bike ownership and car ownership are negatively correlated with bike use. Additionally, students use bikes more frequently than other occupational groups, and people with higher education levels also use bikes more. These groups may be interrelated. It's also noteworthy that in 2019, the influence of student status on bike use was even stronger.

The primary predictors of car use are high educated, male car owners who are employed. Although we have seen earlier that older individuals tend to own cars to a greater extent, they use them less frequently than younger individuals. Furthermore, people in rural areas use cars more than those in urban areas. Additionally, household income is positively correlated with car use, indicating that wealthier individuals use their cars more.

Public transport (PT) use is significantly lower among car owners and a little higher among conventional bike owners. Moreover, especially students use PT more than other occupational groups but also working people use PT more. Higher education levels correlate positive with increased PT use. It seems that the older people get, they tend to use PT less. Lastly, the number of household members is negatively correlated with PT use meaning that larger households will use PT less.

Next, it is important to critically reflect on the substitution effect observed in this study, considering the results discussed above. Given that e-bike ownership is the strongest predictor of e-bike use, it is evident that owning an e-bike significantly increases the likelihood of using it. Additionally, the analysis reveals that e-bike ownership is negatively correlated with both car use and conventional bike use, suggesting a substitution effect. In summary, e-bike ownership appears to shift travel behaviour, substituting not only for conventional cycling but also, to some extent, for car use, highlighting its potential role in promoting more sustainable transport options.

What social demographics affect the vehicle ownership?

While addressing the first research question on how vehicle ownership influences travel behaviour, it is important to first understand how vehicle ownership itself is shaped by social demographics. Let's begin examining how social demographics influence vehicle ownership. In this analysis, the primarily focus lies on the Exp(B) result, also known as the odds ratio. Exp(B) represents the ratio-change in the odds of the event of interest for a one-unit change in the predictor. Table 6 below shows the results and B.1 SD on ownership will provide a more detailed result. The coefficients that are not statistically significant are highlighted in red. First the e-bike will be discussed, then the conventional bike and lastly the car.

Regarding e-bike ownership, women have higher odds of owning an e-bike. The older people get, the higher odds of owning an e-bike, especially people of the age 50 plus. Retired people also have a higher odd of owning an e-bike. Viewing the education level, individuals with high education levels have lower odds of e-bike ownership compared to those with low education level. Household income is slightly positive with e-bike ownership, which indicates that higher household income is associated with an increase in the odds of e-bike ownership.

Looking at the ownership of conventional bikes, older people (50+) are less likely to own a conventional bike. Also, people with driving licence are less likely to own a conventional bike. Students have a higher odd of owning a conventional bike. Moreover, the higher the level of education, the higher the odds of owning a conventional bike.

Interestingly, when analysing car ownership, the exp(B) suggests that females have slightly higher odds of car ownership compared to males, but the result in 2019 is not statistically significant, so this seems like a weaker effect. The older people get, the higher chance of owning a car. Logically, people with a driving license have a much-increased odds of car ownership. Regarding main occupation status, working and retired individuals have higher odds of owning a car, while student have lower odds. The number of household members is positive correlated with car-ownership, this suggests that each additional person in the household increases the odds of car ownership. Furthermore, people living in a rural area have increased odds of car ownership.

Social demographics play a significant role in vehicle ownership, with different factors influencing e-bike, conventional bike, and car ownership in distinct ways. Women, older individuals, and retirees are more likely to own an e-bike, while higher education reduces the likelihood of e-bike ownership. Conventional bike ownership is more common among students and those with higher education, but less likely among older individuals. Car ownership is mainly influenced by driving license possession and by age, retired people, household size, and rural residency.

Table 6: Odds ratio

Odds Ratio		Vehicle ownership					
		Car ownership		E-Bike ownership		Bike ownership	
		Exp(B)	**P-value**	**Exp(B)**	**P-value**	**Exp(B)**	**P-value**
Gender (reference = male)	Female	1.29	0.02	1.70	0.00	0.85	0.07
Age (reference = 12 - 29)	30 - 49	2.17	0.00	2.47	0.00	0.80	0.13
	50 +	3.46	0.00	8.42	0.00	0.48	0.00
License ownership		4.481	0.00	1.36	0.05	0.71	0.01
Primary occupation (reference = other)	Working	3.24	0.00	0.79	0.11	1.11	0.38
	Retired	2.86	0.00	1.37	0.02	0.86	0.22
	Student	0.35	0.00	0.56	0.16	4.11	0.00
Education level (reference = low)	Medium	0.96	0.76	1.02	0.88	1.44	0.00
	High	0.94	0.69	0.72	0.02	1.98	0.00

Household income		1.06	0.10	1.07	0.04	1.01	0.79
Number of persons in household		1.34	0.00	1.08	0.21	0.95	0.23
Urbanity (rural is higher)		1.32	0.00	1.06	0.13	0.96	0.23
Nagelkerke R Square		0.56		0.22		0.14	

4.1.2 Moderating role of car attitude

- To what extent does the attitude towards the car moderate the relationship between e-bike ownership and the use of different modes?

In the following results are car attitudes included in the analysis. As the conceptual models showed in 2.4, the following analysis considers the direct influence of car attitude on travel behaviour and how car attitude moderate the relationship between e-bike ownership and travel behaviour. In Table 7 below are the results presented. B.4 Attitudes in the appendix shows the results with more details.

Firstly, car attitude correlates negatively with bike use and PT use and positively with car use. This indicates that people who have a positive attitude towards cars, travel less by bike and PT. Evidentially, people who are positive towards cars, travel more by car. Secondly, a significant result shows a negative moderating effect of car attitude among e-bike owners which means that e-bike owners who hold a positive attitude towards cars tend to use their e-bikes less. This negative interaction effect implies that a positive attitude towards cars weakens the expected increase in e-bike use that typically comes with e-bike ownership. It is noteworthy that the other interaction effect is not significant, especially for bike sue and car use. This implies that car attitude does not moderate the relationship of e-bike ownership and the usage of bike and car. The absence of significant interaction effects suggests that individuals' attitudes towards cars may not substantially influence their choices regarding e-bike ownership and the corresponding use of alternative modes of transportation.

There are other remaining results concerning this analysis. Firstly, e-bike ownership is still the largest predictor of e-bike use. Firstly, e-bike ownership does not have a significant effect on bike use anymore, while the last analysis indicated a negative correlation. Thirdly, as mentioned above, people with a positive attitude towards cars, will use the car more. However, the magnitude of the effect does not seem large when viewing the standardised coefficients. Gender, occupation and education level have a larger effect on car use.

Overall, this analysis highlights the significant role of attitudes towards cars in shaping travel behaviour. Firstly, e-bike owners who have a positive attitude towards cars are less likely to use their e-bikes as a mode of transport. Secondly, e-bike ownership no longer correlates with bike use, while attitudes towards cars now offer a better explanation for bike use. This trend is also observed with car use. These findings suggest that the substitution effect of e-bike ownership may be weaker than previously thought, with attitudes towards cars providing a more comprehensive explanation of travel behaviour.

To give these results more context and perspective, correlations between car attitude and social demographics are calculated. The strongest correlation is observed with license ownership, suggesting that most people owning a license also have a positive car attitude. Other variables like household income, working status, and household size show moderate positive correlations, whereas variables like retirement and people aged 50+ have negative correlations. Gender, age 30-49, and urbanisation show smaller but significant correlations. This indicates that males, people in their 30 to 49 and people in more rural areas have a more positive attitude towards cars.

Table 7: Results including attitudes

Standardized Coefficients		Use per mode							
		E-bike use		Bike use		Car use		PT use	
		Beta	**P-value**	**Beta**	**P-value**	**Beta**	**P-value**	**Beta**	**P-value**
Car ownership		-0.01	0.47	-0.04	0.07	0.17	0.00	-0.13	0.00
Conventional bike ownership		0.02	0.33	0.12	0.00	-0.02	0.37	0.05	0.01
E-bike ownership		1.06	0.00	-0.13	0.05	0.01	0.90	-0.06	0.49
Attitude car		-0.01	0.80	-0.06	0.00	0.08	0.00	-0.05	0.01
Interaction e-bike ownership and attitude		-0.68	0.00	0.07	0.43	-0.04	0.67	0.07	0.45
Gender (reference = male)	Female	-0.01	0.49	-0.01	0.49	-0.12	0.00	-0.01	0.47
Age (reference = 12 - 29)	30 - 49	0.01	0.76	0.00	0.94	-0.02	0.60	-0.08	0.02
	50 +	0.03	0.41	0.01	0.77	-0.07	0.06	-0.11	0.00
License ownership		0.02	0.25	0.04	0.06	0.02	0.22	0.01	0.53
Primary occupation (reference = other)	Working	0.04	0.07	0.02	0.44	0.13	0.00	0.11	0.00
	Student	0.01	0.51	0.04	0.03	-0.01	0.52	0.12	0.00
	Retired	0.04	0.11	0.04	0.08	0.02	0.47	0.07	0.00
Education level (reference = low)	Medium	0.00	0.87	0.00	0.85	0.07	0.00	0.03	0.14
	High	0.00	0.82	0.07	0.00	0.13	0.00	0.09	0.00
Household income		0.00	0.97	-0.01	0.53	0.02	0.22	-0.01	0.77
Urbanity (rural is higher)		0.00	0.81	-0.03	0.11	0.05	0.00	0.00	0.84
Number of persons in household		0.00	0.85	0.00	0.83	-0.05	0.01	-0.05	0.01
R-square		0.18		0.04		0.13		0.07	

4.1.3 Impact of e-bike purchase over time

- To what extent does the purchase of the e-bike influence the use of different travel modes over time?

Now, the results of the DID method are presented to answer the above research question. Thus, both 2018 and 2019 data are used for this purpose. Table 8 shows the results. The red value indicates an insignificant value.

The change in e-bike ownership significantly predicts the change in e-bike use, suggesting that as e-bike ownership increases, the distance travelled using e-bikes also increases. The change in e-bike ownership does not significantly predict changes in the use of cars, conventional bikes, or public transport. These results can be interpreted as indicating that increased e-bike ownership primarily affects e-bike usage, without significant displacement of other travel modes such as car use, conventional bike use, or public transport.

Table 8: Results Difference-in-Differences analysis

	Unstandardized Coefficients		Standardized Coefficients		
	B	Std. Error	Beta	t	Sig.
Dependent Variable: delta use car					
Constant	48.7	1.5		33.13	0.000
delta E-bike ownership	3.4	5.8	0.009	0.58	0.562
Dependent Variable: delta use conventional bike					
Constant	5.3	0.3		16.74	0.000
delta E-bike ownership	1.3	1.3	0.015	1.00	0.319
Dependent Variable: delta use e-bike					
Constant	2.9	0.3		10.18	0.000
delta E-bike ownership	7.5	1.2	0.100	6.50	0.000
Dependent Variable: delta use PT					
Constant	64.6	3.6		17.91	0.000
delta E-bike ownership	-0.3	14.4	0.000	-0.02	0.983

The Difference-in-Differences (DID) analysis was focussed on the group within the population who purchased an e-bike. Table 9 presents four distinct groups identified within the data. To conduct a more in-depth analysis, this research will examine these four groups to assess the degree of heterogeneity within the population.

These groups are categorized based on e-bike ownership status: one group consists of individuals who purchased an e-bike in 2019, while another group includes those who disposed of their e-bike during the same year. Additionally, there is a group of individuals who still do not own an e-bike, and another group that continues to possess an e-bike. An important group in the light of this study are those who have bought an e-bike, which is 6.3% of the population.

For each of these four groups, paired t-tests will be conducted to compare the means of two related groups. This statistical test evaluates whether the average difference in distance travelled (mode use) for each mode of transport between 2018 and 2019 is significantly different from zero. This analysis will help to understand any changes in usage patterns between the two years. Table 10 shows the results of the paired t-tests. More detailed results are presented in appendix B.5 Paired T-tests. The mean difference column shows the average change in distance travelled between 2018 and 2019 for each mode of transport. A positive value means the distance travelled increased in 2019 compared to 2018, and a negative value means it decreased. The two-sided p-value shows the statistical significance of the difference. If the p-value is less than 0.05, there is a statistically significant difference in the distances travelled between 2018 and 2019.

A very essential result is that there is a significant decrease in the distance travelled by bike between 2018 and 2019, for the people that purchased an e-bike. This implies that the purchase of an e-bike in fact does reduces the use of a conventional bike. It is noteworthy that car use is just not significant and e-bike purchase does not indicate car use reduces. Furthermore, in line of expectation, the distance travelled by e-bike increased for e-bike purchasers. Then, people who discard their e-bike, travel less by the e-bike. Interestingly enough, non of the other use of travel mode does replace the e-bike, because the other mean differences are not significant.

Next, the two groups whose e-bike ownership status remained unchanged will be examined. The people who still have no e-bike is the largest group with 72.2%. A remarkable result is that there is a small e-bike increase among this group. This could be explained by people using shared e-bike or the fact that this group does not owning an e-bike but burrows an e-bike. Furthermore, there is a decrease in the use of a conventional bike between 2018 and 2019. Another important and remarkable finding in the group of individuals who owned an e-bike in both 2018 and 2019 is that their use of the e-bike decreased significantly over the two years. Moreover, compared to the group that purchased an e-bike in 2019, this group did not reduce their usage of conventional bikes.

Table 9: Distinction of 4 groups

Distribution		
Purchased e-bike	%	6.3
Discarded e-bike	%	2.1
Still no e-bike	%	72.2
Still have an e-bike	%	19.4

Table 10: Paired T-tests

Purchased e-bike		
Use 2019 -2018	Mean difference	Two-sided p
Car	-12.25	0.088
Bike	-4.51	0.007
E-bike	6.61	0.047
PT	-18.53	0.233

Discarded e-bike		
Use 2019 -2018	Mean difference	Two-Sided p
Car	5.07	0.582
Bike	-1.06	0.523
E-bike	-5.02	0.001
PT	-36.55	0.075

Still no e-bike

Use 2019 -2018	Mean difference	Two-Sided p
Car	-1.42	0.460
Bike	-1.21	0.002
E-bike	0.20	0.018
PT	-5.28	0.218

Still have an e-bike		
Use 2019 -2018	Mean difference	Two-Sided p
Car	-4.40	0.199
Bike	-0.73	0.076
E-bike	-3.86	0.000
PT	-1.68	0.835

4.2 Discussion

The discussion will interpret the significance of the findings in a broader context and relate it to previous research. This subchapter involves explaining the significance of the results, relating them to previous studies and acknowledging any limitations. First, the main take aways from the results are formulated and compared to existing research.

A negative moderating effect of car attitude is observed, meaning e-bike owners who have a positive attitude towards cars tend to use their e-bikes less. This highlights how attitudes towards cars can diminish the substitution effect of e-bike ownership. Additionally, other moderating effects of attitude are not significant, suggesting that the assumption that individuals with pro-car attitudes are more likely to use e-bikes as a substitute for bicycles, while those with anti-car attitudes tend to use e-bikes to replace car trips, is not supported by these results. The direct influence of attitude on travel behaviour shows a more substantial effect.

E-bike ownership shows a negative correlation with both car use and conventional bike use in some analyses, suggesting a substitution effect, where people replace trips made by car or bikes with e-bikes. However, in other analyses, e-bike ownership no longer correlates significantly with bike use, and its correlation with car use weakens or also becomes insignificant. Although the results are not entirely conclusive, the e-bike appears to replace the conventional bike to a greater extent than it does the car. This suggests that the substitution effect may not be as strong as previously thought, and attitudes towards cars play a larger role in determining travel behaviour.

The differences in findings between the multiple regression, DID, and paired t-tests arise from the specific focus, variables included, and analytical assumptions of each method. The multiple regression examines the cross-sectional relationships between e-bike ownership, car attitudes, and travel behaviour at one point in time, controlling for demographic factors. The DID evaluates the causal impact of purchasing an e-bike by comparing travel behaviour before and after the purchase, relative to a control group that did not purchase one. The paired t-test captures within-group changes by comparing the differences in the distance travelled by different modes between 2018 and 2019. All analyses had another purpose offering a perspective on e-bike ownership and travel behaviour.

Comparison to existing literature

In order to situate the findings within the context of existing research, the results are discussed and compared with or contradict previous studies, and what new insights this research adds to the field. There are multiple findings consistent with previous literature. First, the substitution effect of e-bikes is observed. The findings suggest that e-bike ownership is negatively correlated with conventional bike use align with Kroesen (2017), who observed that e-bikes primarily replace conventional bikes rather than other modes. This supports the idea that in countries like the Netherlands, where cycling is dominant, e-bikes act more as a substitute for regular bikes than for cars. The analyses suggest that e-bikes have a partial substitution effect on car use, although this effect diminishes over time. This is consistent with De Kruijf et al. (2018), who found that e-bikes replaced car and bike trips equally. Similarly, Plazier et al. (2017a) demonstrated that e-bikes can replace motorized transport, particularly for commuting, suggesting that the e-bike's role as a car substitute is context-dependent, especially for work-related travel.

Furthermore, the results emphasize the moderating effect of car attitudes on e-bike use, which aligns with studies such as De Vos et al. (2022). These studies indicate that individuals with positive attitudes towards cars are less likely to adopt alternative modes like e-bikes. This reinforces the view that travel behaviour is not only influenced by ownership but also by attitudinal preferences toward specific travel modes.

An important contribution of this research is the finding that car attitudes play a more substantial role in determining e-bike use than ownership itself. While previous studies (De Vos et al., 2022) have examined attitudes in travel mode choice, our research adds a new dimension by showing that pro-car attitudes significantly diminish the likelihood of using an e-bike, even among owners. This suggests that merely promoting e-bike ownership is not enough to drive substantial changes in travel behaviour, deeper attitudinal shifts are necessary. Next, the insights from this research that differ from existing studies will be discussed. Contrary to earlier studies, such as those by Plazier et al. (2017a), which suggested that e-bikes could significantly replace car trips, the findings of this research show that the correlation between e-bike ownership and car use weakens or becomes insignificant over time.

Broader discussion

Now, the findings offer several broader implications for the fields of travel behaviour, policymaking, and infrastructure. The results will be discussed to their broader meaning and relevance by taking into account theory, practice and policymaking.

The research shows that people who value cars are less likely to use e-bikes, even if they own one. This suggests that promoting e-bike ownership alone may not be sufficient to encourage sustainable travel behaviour. It is crucial to consider the heterogeneity in travel attitudes, particularly among commuters. Future research should focus on understanding the attitudes of different subgroups, as this could provide further insights into how to effectively promote e-bike use among car owners.

The findings are highly relevant for policymakers and urban planners. If e-bike ownership strongly correlates with e-bike use, policies that promote ownership—through subsidies, incentives, or expanding cycling infrastructure—could encourage more sustainable travel behaviour. However, the moderating effect of car attitudes suggests that simply increasing e-bike availability will not shift behaviour significantly. Policymakers must also address cultural and attitudinal barriers, perhaps through awareness campaigns or urban designs that make non-car travel more appealing.

Currently, regulations regarding e-bikes are in progress. The upcoming helmet regulations and age restrictions for e-bike users in the Netherlands may negatively impact e-bike adoption, similar to the decline in moped use following the introduction of regulations in 2023. Additionally, cities are increasingly discouraging car use and promoting cycling by implementing measures such as car-free zones, higher parking fees, and expanded cycling infrastructure. These changes to the built environment could indirectly encourage e-bike adoption and reinforce the shift towards more active travel modes.

An important factor in travel behaviour is the built environment, particularly residential self-selection, where people choose where to live based on their travel preferences and needs. Studies have shown an interdependent relationship between travel attitudes, the built environment, and travel behaviour. For example, moving to a more urban area might stimulate active travel, partly by improving attitudes toward non-car modes. This further supports the need for urban planning that fosters active travel environments and aligns with people's attitudes toward sustainable transportation.

Travel mode choice is influenced by various factors, including the characteristics of the trip itself (e.g., cost, time, route), weather conditions, and personal preferences. While the e-bike may be an attractive alternative to the car, adverse weather conditions may still lead individuals to choose cars. Understanding these behavioural nuances is essential for developing policies and interventions that effectively encourage the use of e-bikes.

Another factor not fully explored in this research is the varying motivations for purchasing an e-bike, which could significantly influence travel behaviour. Different types of e-bike users may have different reasons for purchasing one, and these motivations could affect their subsequent use of the bike. Future research should investigate these motivations to provide a deeper understanding of the relationship between e-bike ownership and travel behaviour.

Limitations

It is important to acknowledge the limitations of this study, including potential constraints such as sample size, data collection methods, and possible biases within the model. Addressing these issues demonstrates transparency about the research's boundaries.

First, when reflecting on causality, it must be considered whether correlation truly implies causation. While the data shows a strong correlation between e-bike ownership and usage, this relationship is likely bi-directional. This means that owning an e-bike increases usage, but frequent usage could also encourage ownership.

Additionally, the conceptual model used in this research could potentially be revised. Alternative pathways might exist. For example, as just mentioned in the previous paragraph, usage could influence ownership decisions. Also, both usage and ownership are likely to be shaped by attitudes towards e-bikes. Moreover, attitudes themselves are crucial factors in shaping travel behaviour, suggesting a more interconnected model.

Another consideration is the presence of unobserved or confounding variables that may influence e-bike ownership, travel behaviour, and underlying attitudes. While this study controlled for several variables, it's possible that other, unmeasured factors play a role. Furthermore, multicollinearity between the interaction terms and attitude variables, especially in relation to car attitude, is a concern that requires careful attention.

A significant demographic change to consider is the rising use of e-bikes, particularly fat bikes, among young people aged 12 to 18. This trend has mainly occurred in recent years. The popularity of e-bikes in this age group might influence broader patterns of travel behaviour, and future research should examine how this trend fits with the findings of this study.

Then, while this study focused on attitudes towards cars, while other attitudinal factors, such as those related to bicycles, e-bikes, public transport, and even the environment, could also play important roles in shaping travel behaviour. A more comprehensive examination of these attitudes could provide a deeper understanding of the factors influencing e-bike adoption and use.

Lastly, several outliers were observed in the data, regarding the distances travelled across different modes of transportation. These outliers may have influenced the results in a significant manner. In this study, these outliers may have skewed the results, potentially leading to misleading interpretations of travel behaviour patterns. The presence of these outliers may be attributed to unique travel circumstances, such as very long commutes or data entry errors.

5. Conclusion

This study set out to explore the relationships between e-bike ownership, car attitude, and their effects on travel mode choices in the Netherlands. The study utilises data from the Mobility Panel of the Netherlands (MPN).

One of the most consistent findings is the strong correlation between e-bike ownership and increased e-bike usage. This supports the idea that simply owning an e-bike substantially increases the likelihood of using it. However, the impact of e-bike ownership on other modes of travel, such as conventional bikes and cars, is more nuanced. Although the results are not entirely conclusive, the e-bike appears to replace the conventional bike to a greater extent than it does the car. In fact, analyses showed minimal evidence of e-bike substituting the car. Conversely, the analysis revealed a more pronounced substitution effect, indicating that e-bikes are effectively replacing conventional bicycle usage.

The study highlights the moderating role of attitudes, particularly toward cars. Individuals with a positive attitude toward cars were less likely to use their e-bikes frequently, even if they owned one, which suggests that attitudes significantly influence travel behaviour. This moderating effect suggests that simply increasing e-bike ownership may not be sufficient to reduce car use, attitudinal shifts are also necessary. These findings align with existing research on travel behaviour, but they offer new insights by emphasizing the importance of car attitudes in shaping e-bike use.

The Difference-in-Differences (DID) and paired t-test analyses provide additional understanding, revealing that those who purchased an e-bike in 2019 reduced their conventional bike use significantly, while changes in car use were not statistically significant. This further supports the notion that e-bikes primarily substitute for bicycles rather than cars in this context. Meanwhile, the group that already owned an e-bike in both 2018 and 2019 saw a decrease in their e-bike use over time, indicating that initial enthusiasm for e-bike use may taper off, particularly among long-term owners.

5.1 Recommendations

Based on the findings of this research, several recommendations can be made to improve policymaking and promote sustainable travel behaviour. These recommendations focus on both policy interventions and strategies to address the barriers that hinder a shift away from car dependence.

Firstly, while promoting e-bike ownership through incentives or subsidies could lead to more sustainable travel choices, it is crucial to address the attitudinal barriers to shifting away from car use. Urban planners should not only focus on increasing e-bike infrastructure but also work on campaigns or interventions that reshape public attitudes toward car usage, especially in car-dependent populations. Advisable is to not only make e-bikes accessible but also change people’s perceptions about them, especially among those who hold positive attitudes toward cars.

Additionally, policies like helmet requirement or age restrictions could impact e-bike adoption, potentially discouraging younger users, a growing demographic of e-bike riders in the Netherlands. Policymakers should assess the potential impact of this shift to better inform future decisions.

Furthermore, given the strong correlation between e-bike ownership and use, policymakers should introduce targeted subsidies or financial incentives, especially for commuters and individuals in suburban or rural areas where car use is higher. This could help drive adoption and reduce car dependence. This could indeed be a strategic consideration, as cost was a significant barrier to purchasing an e-bike.

5.2 Reflection

Here follows a reflection containing the limitations of this research and suggestions for future research.

Limitations

The data utilized for this research was not the most current; unfortunately, more recent data could not be employed due to the impact of COVID-19 and related to data availability. Access to this more recent data could have provided a more accurate and up-to-date picture of the current transportation landscape, especially given the rapid developments in e-bike ownership and use, particularly among younger individuals (ages 12-18).

By adding the attitudes, this research tries to account for heterogeneity in the observed group. However, the methods used in this research assume the same effects across all individuals. There may be other variables that influence both attitudes and travel behaviour but are not included in the analysis, leading to biased estimates. For example, built environment is known for a significant role in travel behaviour and attitude.

In this research, public transport modes (including bus, tram, metro, and train) were grouped together. However, these modes have distinct characteristics that could have influenced the results. Analysing them separately, particularly isolating the train from the other three modes, could provide more nuanced insights.

People who are living in rural areas are underrepresented compared to the actual data and people who are ling in very urban areas are overrepresented compared to the actual data. If the sample predominantly includes urban residents, the results may reflect urban travel behaviours and attitudes toward e-bikes more than those of rural residents.

Future research

Future studies should utilise the most recent data available to capture current trends in transportation behaviour more accurately. This would also enhance understanding of emerging user groups, such as younger individuals increasingly adopting e-bikes.

Conduct research with a method which can deal well with heterogeneity. This is particularly useful when analysing panel data, where you have multiple observations over time for the same individuals. For example, fixed effects model addresses the issue of omitted variable bias by controlling for all time-invariant characteristics of the units being studied, whether these characteristics are observed or unobserved.

Further research should delve into the relationship between attitudes and e-bike use, examining how different attitudes influence the adoption and usage patterns of e-bikes across various demographic groups. Also, people's attitudes towards e-bikes should be explored, or other attitudes like public transport, and how these attitudes influence their travel behaviour.

Understanding these factors could provide clearer insights into why individuals choose certain modes of transport and help identify strategies to encourage e-bike adoption.

Conducting research that differentiates between various public transport modes (such as bus, tram, metro, and train) would allow for a deeper understanding of the unique factors influencing the use of each mode. It is plausible that due to varying characteristics, such as distance travelled, trains may show different patterns of usage compared to trams and buses.

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Appendices

Appendix A: Dummy codes scheme

Gender	Female		
Male	0		
Female	1		
Age	**30 - 49**	**50+**	
12 - 29 years	0	0	
30-49 years	1	0	
50+ years	0	1	
Education level	**Medium**	**High**	
Low	0	0	
Medium	1	0	
High	0	1	
Primary occupation	**Working**	**Retired**	**Student**
Other	0	0	0
Working	1	0	0
Retired	0	1	0
Student	0	0	1

Appendix B: Results

B.1 SD on ownership

2018

		B	S.E.	Wald	df	Sig.	Exp(B)
Car ownership							
Gender (reference = male)	Female	0.25	0.11	5.27	1	0.02	1.29
Age (reference = 12 - 29)	30 - 49	0.77	0.16	23.36	1	0.00	2.17
	50 +	1.24	0.19	44.87	1	0.00	3.46
License ownership		4.48	0.27	277.79	1	0.00	88.36
Primary occupation (reference = other)	Working	1.18	0.15	62.69	1	0.00	3.24
	Retired	1.05	0.17	37.35	1	0.00	2.86
	Student	-1.06	0.26	16.04	1	0.00	0.35
Education level (reference = low)	Medium	-0.04	0.14	0.09	1	0.76	0.96
	High	-0.06	0.15	0.16	1	0.69	0.94

Household income		0.06	0.03	2.78	1	0.10	1.06
Number of persons in household		0.29	0.06	25.46	1	0.00	1.34
Urbanity (rural is higher)		0.27	0.04	37.66	1	0.00	1.32
Constant		-6.25	0.38	266.41	1	0.00	0.00

E-bike ownership							
Gender (reference = male)	Female	0.53	0.11	21.94	1	0.00	1.70
Age (reference = 12 - 29)	30 - 49	0.91	0.29	9.59	1	0.00	2.47
	50 +	2.13	0.29	53.44	1	0.00	8.42
License ownership		0.30	0.16	3.76	1	0.05	1.36
Primary occupation (reference = other)	Working	-0.23	0.14	2.60	1	0.11	0.79
	Retired	0.32	0.14	5.43	1	0.02	1.37
	Student	-0.57	0.41	1.96	1	0.16	0.56
Education level (reference = low)	Medium	0.02	0.12	0.02	1	0.88	1.02
	High	-0.33	0.14	5.47	1	0.02	0.72
Household income		0.07	0.04	4.19	1	0.04	1.07
Number of persons in household		0.08	0.06	1.55	1	0.21	1.08
Urbanity (rural is higher)		0.06	0.04	2.25	1	0.13	1.06
Constant		-3.95	0.37	114.24	1	0.00	0.02

Conventional bike ownership							
Gender (reference = male)	Female	-0.16	0.09	3.26	1	0.07	0.85
Age (reference = 12 - 29)	30 - 49	-0.23	0.15	2.28	1	0.13	0.80
	50 +	-0.74	0.16	21.45	1	0.00	0.48
License ownership		-0.35	0.13	7.34	1	0.01	0.71
Primary occupation (reference = other)	Working	0.10	0.12	0.78	1	0.38	1.11
	Retired	-0.15	0.12	1.52	1	0.22	0.86
	Student	1.41	0.25	33.23	1	0.00	4.11
Education level (reference = low)	Medium	0.36	0.10	12.39	1	0.00	1.44
	High	0.68	0.12	34.56	1	0.00	1.98
Household income		0.01	0.03	0.07	1	0.79	1.01
Number of persons in household		-0.05	0.04	1.46	1	0.23	0.95
Urbanity (rural is higher)		-0.04	0.03	1.44	1	0.23	0.96
Constant		1.24	0.23	28.84	1	0.00	3.45

2019

		B	S.E.	Wald	df	Sig.	Exp(B)
Car ownership							
Gender (reference = male)	Female	0.07	0.09	0.64	1	0.42	1.07
Age (reference = 12 - 29)	30 - 49	0.67	0.13	24.63	1	0.00	1.95
	50 +	1.13	0.15	59.60	1	0.00	3.09
License ownership		3.93	0.17	516.02	1	0.00	51.14
Primary occupation (reference = other)	Working	0.75	0.12	39.97	1	0.00	2.11
	Retired	0.79	0.14	31.84	1	0.00	2.19
	Student	-1.91	0.22	73.91	1	0.00	0.15
Education level (reference = low)	Medium	0.21	0.11	3.68	1	0.05	1.23
	High	0.06	0.12	0.28	1	0.60	1.06
Household income		0.05	0.03	4.02	1	0.04	1.05
Number of persons in household		0.28	0.04	56.28	1	0.00	1.33
Urbanity (rural is higher)		0.25	0.04	49.05	1	0.00	1.28
Constant		-5.15	0.28	342.83	1	0.00	0.01
E-bike ownership							
Gender (reference = male)	Female	0.50	0.07	50.42	1	0.00	1.65
Age (reference = 12 - 29)	30 - 49	0.89	0.19	21.93	1	0.00	2.42
	50 +	1.83	0.19	95.48	1	0.00	6.22
License ownership		0.38	0.12	9.84	1	0.00	1.47
Primary occupation (reference = other)	Working	-0.01	0.10	0.02	1	0.89	0.99
	Retired	0.57	0.10	30.20	1	0.00	1.77
	Student	-0.10	0.26	0.15	1	0.70	0.90
Education level (reference = low)	Medium	0.14	0.08	2.64	1	0.10	1.15
	High	-0.25	0.10	6.74	1	0.01	0.78
Household income		0.05	0.02	6.01	1	0.01	1.05
Number of persons in household		0.01	0.03	0.12	1	0.73	1.01
Urbanity (rural is higher)		0.07	0.03	6.52	1	0.01	1.07
Constant		-3.56	0.25	198.29	1	0.00	0.03
Conventional bike ownership							
Gender (reference = male)	Female	-0.14	0.06	5.02	1	0.03	0.87

Age (reference = 12 - 29)	30 - 49	0.09	0.12	0.55	1	0.46	1.09
	50 +	-0.48	0.12	16.27	1	0.00	0.62
License ownership		-0.31	0.10	8.87	1	0.00	0.73
Primary occupation (reference = other)	Working	0.33	0.09	14.14	1	0.00	1.39
	Retired	-0.18	0.10	3.60	1	0.06	0.83
	Student	1.53	0.19	66.11	1	0.00	4.63
Education level (reference = low)	Medium	0.24	0.08	9.98	1	0.00	1.27
	High	0.67	0.09	60.49	1	0.00	1.95
Household income		0.02	0.02	1.72	1	0.19	1.02
Number of persons in household		-0.05	0.03	3.12	1	0.08	0.95
Urbanity (rural is higher)		0.00	0.02	0.03	1	0.87	1.00
Constant		0.69	0.18	14.77	1	0.00	2.00

B.2 Ownership on use

2018

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
Dependent Variable: Car use					
Constant	11.60	3.24		3.58	0.00
Car ownership	62.65	2.77	0.28	22.64	0.00
E-bike ownership	-16.41	3.32	-0.06	-4.94	0.00
Conventional bike ownership	4.10	2.81	0.02	1.46	0.15

Dependent Variable: Bike use					
Constant	5.72	0.54		10.55	0.00
Car ownership	-3.44	0.46	-0.09	-7.42	0.00
E-bike ownership	-2.61	0.56	-0.06	-4.70	0.00
Conventional bike ownership	5.08	0.47	0.14	10.79	0.00

Dependent Variable: E-bike use					
Constant	0.81	0.35		2.32	0.02
Car ownership	-0.55	0.30	-0.02	-1.83	0.07
E-bike ownership	10.36	0.36	0.36	28.83	0.00
Conventional bike ownership	-0.11	0.30	0.00	-0.35	0.72

Dependent Variable: PT use					
Constant	93.27	7.15		13.05	0.00
Car ownership	-74.09	6.11	-0.15	-12.13	0.00
E-bike ownership	-13.74	7.33	-0.02	-1.87	0.06
Conventional bike ownership	30.63	6.21	0.07	4.93	0.00

2019

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
Dependent Variable: Car use					
Constant	11.94	3.26		3.67	0.00
Car ownership	58.45	2.81	0.28	20.77	0.00
E-bike ownership	-16.46	3.10	-0.07	-5.30	0.00
Conventional bike ownership	7.73	2.80	0.04	2.76	0.01

Dependent Variable: Bike use					
Constant	6.08	0.60		10.14	0.00
Car ownership	-4.64	0.52	-0.12	-8.96	0.00
E-bike ownership	-2.48	0.57	-0.06	-4.35	0.00
Conventional bike ownership	4.15	0.51	0.11	8.05	0.00

Dependent Variable: E-bike use					
Constant	0.30	0.52		0.58	0.56
Car ownership	-0.73	0.45	-0.02	-1.62	0.11
E-bike ownership	8.60	0.50	0.24	17.35	0.00
Conventional bike ownership	0.71	0.45	0.02	1.60	0.11

Dependent Variable: PT use					
Constant	85.00	7.37		11.53	0.00
Car ownership	-70.88	6.37	-0.15	-11.13	0.00
E-bike ownership	-6.54	7.02	-0.01	-0.93	0.35
Conventional bike ownership	32.17	6.33	0.07	5.08	0.00

B.3 Ownership on use (controlling for SD)

2018

		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
Dependent Variable: Car use						
Constant		-2.03	11.91		-0.17	0.86
Car ownership		48.72	5.30	0.18	9.19	0.00
E-bike ownership		-8.82	4.86	-0.03	-1.81	0.07
Conventional bike ownership		-4.79	4.14	-0.02	-1.16	0.25
Gender (reference = male)	Female	-25.81	3.94	-0.11	-6.55	0.00
Age (reference = 12 - 29)	30 - 49	-8.37	7.82	-0.04	-1.07	0.28
	50 +	-20.54	8.17	-0.09	-2.51	0.01
License ownership		12.62	7.57	0.03	1.67	0.10
Primary occupation (reference = other)	Working	28.86	5.51	0.13	5.24	0.00
	Retired	2.38	6.15	0.01	0.39	0.70
	Student	-7.67	16.31	-0.01	-0.47	0.64
Education level (reference = low)	Medium	16.40	4.92	0.07	3.33	0.00
	High	26.64	5.28	0.11	5.04	0.00
Household income		4.84	1.22	0.07	3.98	0.00
Urbanity (rural is higher)		5.36	1.53	0.06	3.51	0.00
Number of persons in household		-4.57	1.61	-0.05	-2.84	0.00

Dependent Variable: Conventional bike use						
Constant		2.65	1.96		1.35	0.18
Car ownership		-2.04	0.87	-0.05	-2.33	0.02
E-bike ownership		-2.41	0.80	-0.06	-3.01	0.00
Conventional bike ownership		4.37	0.68	0.12	6.41	0.00
Gender (reference = male)	Female	-0.32	0.65	-0.01	-0.49	0.62
Age (reference = 12 - 29)	30 - 49	0.28	1.29	0.01	0.21	0.83
	50 +	0.54	1.34	0.02	0.40	0.69
License ownership		1.93	1.25	0.03	1.55	0.12
Primary occupation (reference = other)	Working	0.51	0.91	0.01	0.57	0.57
	Retired	1.87	1.01	0.05	1.84	0.07
	Student	5.62	2.69	0.04	2.09	0.04

Education level (reference = low)	Medium	0.00	0.81	0.00	0.01	1.00
	High	2.41	0.87	0.07	2.77	0.01
Household income		0.01	0.20	0.00	0.03	0.97
Urbanity (rural is higher)		-0.43	0.25	-0.03	-1.72	0.08
Number of persons in household		-0.11	0.27	-0.01	-0.40	0.69

Dependent Variable: E-bike use						
Constant		-0.72	1.07		-0.67	0.50
Car ownership		-0.56	0.48	-0.02	-1.18	0.24
E-bike ownership		10.07	0.44	0.39	23.02	0.00
Conventional bike ownership		0.31	0.37	0.01	0.85	0.40
Gender (reference = male)	Female	-0.21	0.35	-0.01	-0.59	0.55
Age (reference = 12 - 29)	30 - 49	0.34	0.70	0.02	0.48	0.63
	50 +	0.67	0.73	0.03	0.92	0.36
License ownership		0.53	0.68	0.01	0.77	0.44
Primary occupation (reference = other)	Working	0.84	0.50	0.04	1.70	0.09
	Retired	0.95	0.55	0.04	1.71	0.09
	Student	0.71	1.47	0.01	0.48	0.63
Education level (reference = low)	Medium	-0.10	0.44	0.00	-0.23	0.82
	High	0.04	0.48	0.00	0.09	0.93
Household income		-0.09	0.11	-0.01	-0.81	0.42
Urbanity (rural is higher)		0.02	0.14	0.00	0.13	0.89
Number of persons in household		-0.05	0.14	-0.01	-0.33	0.74

Dependent Variable: PT use						
Constant		88.99	24.42		3.64	0.00
Car ownership		-74.22	10.89	-0.14	-6.82	0.00
E-bike ownership		2.84	9.98	0.01	0.28	0.78
Conventional bike ownership		22.83	8.49	0.05	2.69	0.01
Gender (reference = male)	Female	-3.66	8.09	-0.01	-0.45	0.65
Age (reference = 12 - 29)	30 - 49	-36.26	16.02	-0.08	-2.26	0.02
	50 +	-49.89	16.74	-0.11	-2.98	0.00
License ownership		4.63	15.54	0.01	0.30	0.77
Primary occupation (reference = other)	Working	48.95	11.30	0.11	4.33	0.00
	Retired	38.47	12.63	0.07	3.04	0.00
	Student	213.42	33.47	0.12	6.38	0.00

Education level (reference = low)	Medium	13.04	10.11	0.03	1.29	0.20
	High	38.29	10.85	0.08	3.53	0.00
Household income		2.15	2.50	0.02	0.86	0.39
Urbanity (rural is higher)		0.36	3.14	0.00	0.12	0.91
Number of persons in household		-9.09	3.31	-0.05	-2.75	0.01

2019

		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
Dependent Variable: Car use						
Constant		-2.34	7.41		-0.32	0.75
Car ownership		36.66	3.60	0.17	10.18	0.00
E-bike ownership		-8.15	3.08	-0.04	-2.65	0.01
Conventional bike ownership		0.07	2.75	0.00	0.03	0.98
Gender (reference = male)	Female	-29.23	2.48	-0.15	-11.79	0.00
Age (reference = 12 - 29)	30 - 49	6.43	4.58	0.03	1.40	0.16
	50 +	-3.55	4.80	-0.02	-0.74	0.46
License ownership		14.88	4.57	0.06	3.26	0.00
Primary occupation (reference = other)	Working	27.33	3.69	0.14	7.41	0.00
	Retired	-6.36	4.21	-0.03	-1.51	0.13
	Student	8.67	6.68	0.03	1.30	0.19
Education level (reference = low)	Medium	5.67	3.14	0.03	1.80	0.07
	High	21.54	3.51	0.10	6.14	0.00
Household income		2.77	0.73	0.05	3.78	0.00
Urbanity (rural is higher)		4.89	0.99	0.06	4.92	0.00
Number of persons in household		-3.26	1.04	-0.05	-3.13	0.00

Dependent Variable: Conventional bike use						
Constant		5.61	1.42		3.95	0.00
Car ownership		-2.49	0.69	-0.06	-3.61	0.00
E-bike ownership		-2.10	0.59	-0.05	-3.56	0.00
Conventional bike ownership		3.63	0.53	0.10	6.90	0.00
Gender (reference = male)	Female	-0.45	0.48	-0.01	-0.95	0.34
Age (reference = 12 - 29)	30 - 49	1.99	0.88	0.05	2.27	0.02
	50 +	1.36	0.92	0.04	1.48	0.14

License ownership		-2.69	0.88	-0.06	-3.07	0.00
Primary occupation (reference = other)	Working	1.49	0.71	0.04	2.11	0.03
	Retired	0.66	0.81	0.02	0.82	0.41
	Student	5.79	1.28	0.10	4.52	0.00
Education level (reference = low)	Medium	-0.60	0.60	-0.02	-1.00	0.32
	High	0.19	0.67	0.01	0.28	0.78
Household income		0.02	0.14	0.00	0.12	0.91
Urbanity (rural is higher)		-0.32	0.19	-0.02	-1.70	0.09
Number of persons in household		-0.05	0.20	0.00	-0.27	0.78

Dependent Variable: E-bike use						
Constant		0.61	1.24		0.49	0.62
Car ownership		-1.20	0.39	-0.05	-3.09	0.00
E-bike ownership		8.47	0.51	0.24	16.46	0.00
Conventional bike ownership		0.73	0.46	0.02	1.60	0.11
Gender (reference = male)	Female	-0.03	0.41	0.00	-0.07	0.94
Age (reference = 12 - 29)	30 - 49	-0.44	0.77	-0.01	-0.57	0.57
	50 +	0.03	0.80	0.00	0.04	0.97
License ownership		-0.22	0.76	-0.01	-0.29	0.77
Primary occupation (reference = other)	Working	0.52	0.62	0.02	0.84	0.40
	Retired	0.68	0.70	0.02	0.97	0.33
	Student	0.19	1.12	0.00	0.17	0.86
Education level (reference = low)	Medium	0.46	0.53	0.01	0.87	0.38
	High	0.45	0.59	0.01	0.76	0.45
Household income		0.02	0.12	0.00	0.17	0.86
Urbanity (rural is higher)		-0.14	0.17	-0.01	-0.87	0.39
Number of persons in household		-0.13	0.17	-0.01	-0.74	0.46

Dependent Variable: PT use						
Constant		58.77	17.24		3.41	0.00
Car ownership		-75.58	8.38	-0.16	-9.02	0.00
E-bike ownership		4.36	7.17	0.01	0.61	0.54
Conventional bike ownership		17.56	6.39	0.04	2.75	0.01
Gender (reference = male)	Female	-4.12	5.77	-0.01	-0.71	0.48
Age (reference = 12 - 29)	30 - 49	-25.03	10.66	-0.05	-2.35	0.02
	50 +	-40.87	11.17	-0.10	-3.66	0.00
License ownership		56.90	10.63	0.10	5.35	0.00

Primary occupation (reference = other)	Working	21.17	8.58	0.05	2.47	0.01
	Retired	13.47	9.79	0.03	1.38	0.17
	Student	91.51	15.55	0.13	5.88	0.00
Education level (reference = low)	Medium	16.03	7.31	0.04	2.19	0.03
	High	48.98	8.16	0.11	6.00	0.00
Household income		3.04	1.71	0.02	1.78	0.08
Urbanity (rural is higher)		-4.71	2.31	-0.03	-2.04	0.04
Number of persons in household		-8.95	2.43	-0.06	-3.69	0.00

B.4 Attitudes

		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
Dependent variable: Car use						
Constant		-38.97	15.67		-2.49	0.01
Car ownership		45.72	5.38	0.17	8.50	0.00
Conventional bike ownership		-3.70	4.13	-0.02	-0.89	0.37
E-bike ownership		3.00	25.00	0.01	0.12	0.90
Attitude car		10.95	2.75	0.08	3.98	0.00
Interaction e-bike ownership and attitude		-2.56	6.08	-0.04	-0.42	0.67
Gender (reference = male)	Female	-26.47	3.92	-0.12	-6.74	0.00
Age (reference = 12 - 29)	30 - 49	-4.09	7.80	-0.02	-0.52	0.60
	50 +	-15.63	8.16	-0.07	-1.92	0.06
License ownership		9.35	7.62	0.02	1.23	0.22
Primary occupation (reference = other)	Working	29.48	5.51	0.13	5.35	0.00
	Student	-10.51	16.30	-0.01	-0.64	0.52
	Retired	4.49	6.14	0.02	0.73	0.47
Education level (reference = low)	Medium	15.82	4.93	0.07	3.21	0.00
	High	29.81	5.21	0.13	5.72	0.00
Household income		1.41	1.14	0.02	1.23	0.22
Urbanity (rural is higher)		4.82	1.53	0.05	3.16	0.00
Number of persons in household		-4.21	1.63	-0.05	-2.59	0.01

Dependent variable: Bike use						
Constant		7.56	2.58		2.93	0.00
Car ownership		-1.58	0.89	-0.04	-1.79	0.07
Conventional bike ownership		4.32	0.68	0.12	6.36	0.00
E-bike ownership		-5.62	4.12	-0.13	-1.37	0.05
Attitude car		-1.31	0.45	-0.06	-2.89	0.00
Interaction e-bike ownership and attitude		0.78	1.00	0.07	0.78	0.43
Gender (reference = male)	Female	-0.45	0.65	-0.01	-0.70	0.49
Age (reference = 12 - 29)	30 - 49	0.10	1.28	0.00	0.08	0.94

	50 +	0.39	1.34	0.01	0.29	0.77
License ownership		2.38	1.26	0.04	1.89	0.06
Primary occupation (reference = other)	Working	0.71	0.91	0.02	0.78	0.44
	Student	5.73	2.68	0.04	2.13	0.03
	Retired	1.80	1.01	0.04	1.77	0.08
Education level (reference = low)	Medium	0.16	0.81	0.00	0.20	0.85
	High	2.55	0.86	0.07	2.98	0.00
Household income		-0.12	0.19	-0.01	-0.63	0.53
Urbanity (rural is higher)		-0.40	0.25	-0.03	-1.59	0.11
Number of persons in household		-0.06	0.27	0.00	-0.22	0.83

Dependent variable: E-bike use						
Constant		-1.24	1.39		-0.89	0.37
Car ownership		-0.35	0.48	-0.01	-0.73	0.47
Conventional bike ownership		0.36	0.37	0.02	0.97	0.33
E-bike ownership		26.99	2.22	1.06	12.14	0.00
Attitude car		-0.06	0.24	0.00	-0.25	0.80
Interaction e-bike ownership and attitude		-4.21	0.54	-0.68	-7.78	0.00
Gender (reference = male)	Female	-0.24	0.35	-0.01	-0.70	0.49
Age (reference = 12 - 29)	30 - 49	0.21	0.69	0.01	0.30	0.76
	50 +	0.59	0.72	0.03	0.82	0.41
License ownership		0.79	0.68	0.02	1.16	0.25
Primary occupation (reference = other)	Working	0.88	0.49	0.04	1.79	0.07
	Student	0.95	1.45	0.01	0.65	0.51
	Retired	0.88	0.55	0.04	1.61	0.11
Education level (reference = low)	Medium	0.07	0.44	0.00	0.17	0.87
	High	0.10	0.46	0.00	0.22	0.82
Household income		0.00	0.10	0.00	0.03	0.97
Urbanity (rural is higher)		0.03	0.14	0.00	0.24	0.81
Number of persons in household		-0.03	0.14	0.00	-0.19	0.85

Dependent variable: PT use						
Constant		144.82	32.14		4.51	0.00
Car ownership		-68.89	11.04	-0.13	-6.24	0.00

Conventional bike ownership		22.68	8.48	0.05	2.68	0.01
E-bike ownership		-35.50	51.29	-0.06	-0.69	0.49
Attitude car		-14.70	5.64	-0.05	-2.61	0.01
Interaction e-bike ownership and attitude		9.47	12.48	0.07	0.76	0.45
Gender (reference = male)	Female	-5.82	8.05	-0.01	-0.72	0.47
Age (reference = 12 - 29)	30 - 49	-37.15	15.98	-0.08	-2.33	0.02
	50 +	-50.41	16.71	-0.11	-3.02	0.00
License ownership		9.85	15.65	0.01	0.63	0.53
Primary occupation (reference = other)	Working	51.82	11.31	0.11	4.58	0.00
	Student	213.99	33.45	0.12	6.40	0.00
	Retired	38.25	12.61	0.07	3.03	0.00
Education level (reference = low)	Medium	15.07	10.12	0.03	1.49	0.14
	High	41.44	10.69	0.09	3.88	0.00
Household income		-0.68	2.34	-0.01	-0.29	0.77
Urbanity (rural is higher)		0.62	3.13	0.00	0.20	0.84
Number of persons in household		-8.34	3.34	-0.05	-2.50	0.01

B.5 Paired T-tests

Purchased e-bike									
	Paired Differences							Significance	
				95% Confidence Interval of the Difference					
Use 2019 -2018	Mean	Std. Deviation	Std. Error Mean	Lower	Upper	t	df	One-Sided p	Two-Sided p
Car	-12.25	115.72	7.15	-26.33	1.83	-1.71	261	0.044	0.088
Bike	-4.51	26.80	1.66	-7.77	-1.25	-2.73	261	0.003	0.007
E-bike	6.61	53.47	3.30	0.10	13.11	2.00	261	0.023	0.047
PT	-18.53	250.88	15.50	-49.05	11.99	-1.20	261	0.116	0.233

Discarded e-bike									
	Paired Differences							Significance	
				95% Confidence Interval of the Difference					
Use 2019 -2018	Mean	Std. Deviation	Std. Error Mean	Lower	Upper	t	df	One-Sided p	Two-Sided p
Car	5.07	86.22	9.19	-13.19	23.34	0.55	87	0.291	0.582
Bike	-1.06	15.42	1.64	-4.32	2.21	-0.64	87	0.261	0.523

E-bike	-5.02	14.02	1.49	-7.99	-2.05	-3.36	87	0.001	0.001
PT	-36.55	190.17	20.27	-76.84	3.75	-1.80	87	0.037	0.075

Still no e-bike									
	Paired Differences							Significance	
				95% Confidence Interval of the Difference					
Use 2019 -2018	Mean	Std. Deviation	Std. Error Mean	Lower	Upper	t	df	One-Sided p	Two-Sided p
Car	-1.42	104.90	1.92	-5.18	2.34	-0.74	2994	0.230	0.460
Bike	-1.21	21.86	0.40	-1.99	-0.43	-3.03	2995	0.001	0.002
E-bike	0.20	4.63	0.08	0.03	0.37	2.37	2995	0.009	0.018
PT	-5.28	234.70	4.29	-13.69	3.12	-1.23	2995	0.109	0.218

Still have an e-bike									
	Paired Differences							Significance	
				95% Confidence Interval of the Difference					
Use 2019 -2018	Mean	Std. Deviation	Std. Error Mean	Lower	Upper	t	df	One-Sided p	Two-Sided p
Car	-4.40	96.95	3.42	-11.10	2.31	-1.29	804	0.099	0.199
Bike	-0.73	11.57	0.41	-1.52	0.07	-1.78	805	0.038	0.076
E-bike	-3.86	26.36	0.93	-5.68	-2.04	-4.16	805	0.000	0.000
PT	-1.68	229.12	8.07	-17.52	14.16	-0.21	805	0.418	0.835

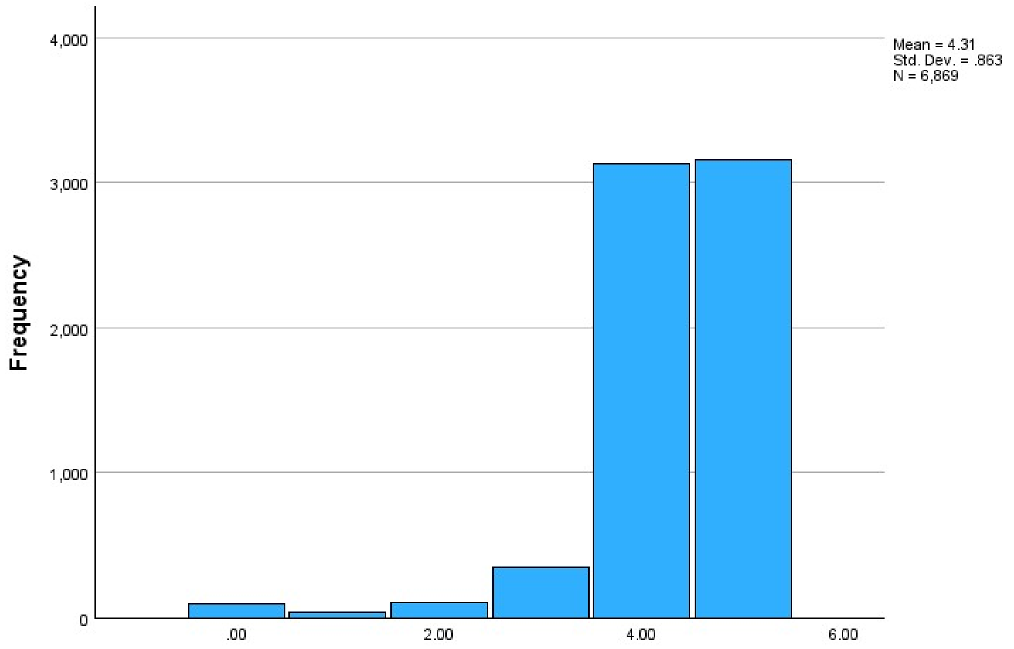
Appendix C: Factor analysis

Communalities		
	Initial	Extraction
I find travelling by car comfortable	0.649	0.708
I find travelling by car comfortable	0.642	0.621
Travelling by car saves me time	0.488	0.504
Travelling by car is safe	0.565	0.620
I find travelling by car flexible	0.612	0.618
Travelling by car is pleasant	0.699	0.746

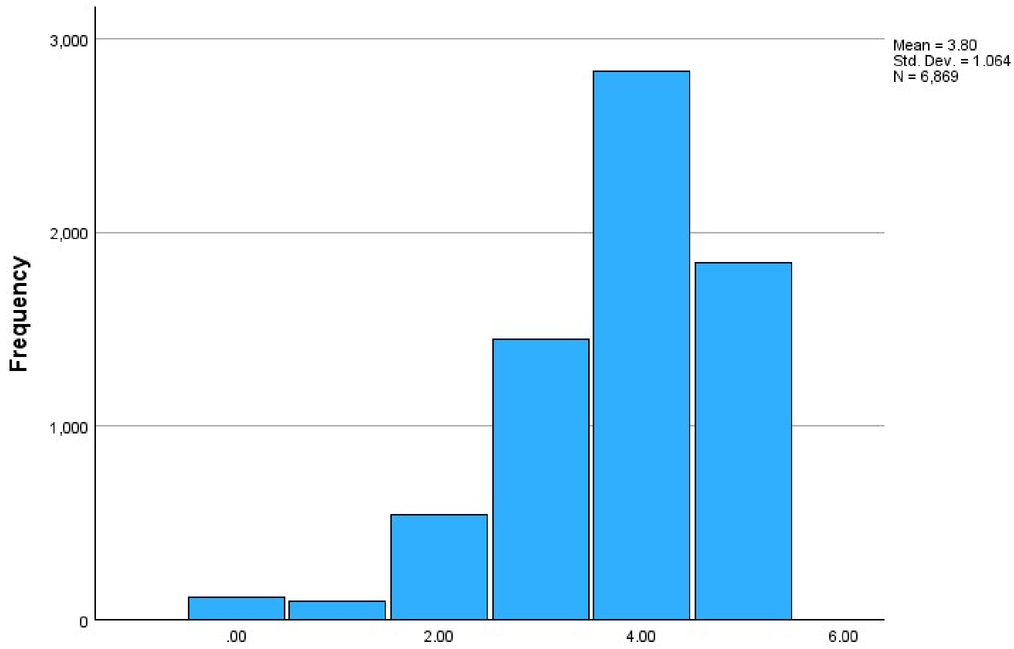
Total Variance Explained						
	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Factor	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	4.173	69.543	69.543	3.816	63.607	63.607
2	0.589	9.816	79.359			
3	0.412	6.869	86.227			
4	0.356	5.933	92.160			
5	0.263	4.391	96.551			
6	0.207	3.449	100.000			
Extraction Method: Principal Axis Factoring.						

Appendix D: Histogram indicators

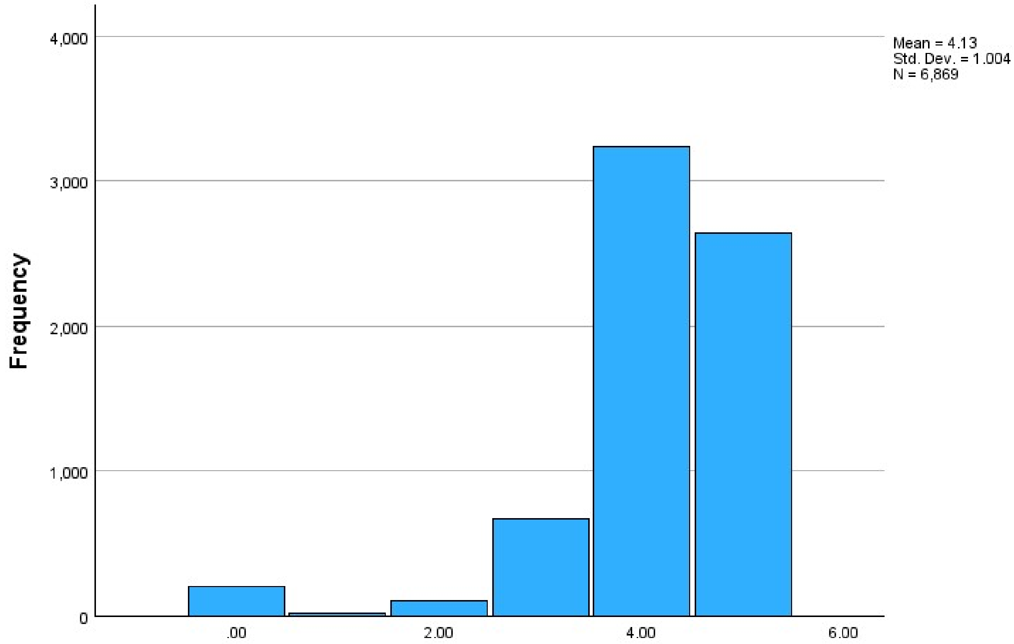
Statement 1: I find travelling by car comfortable



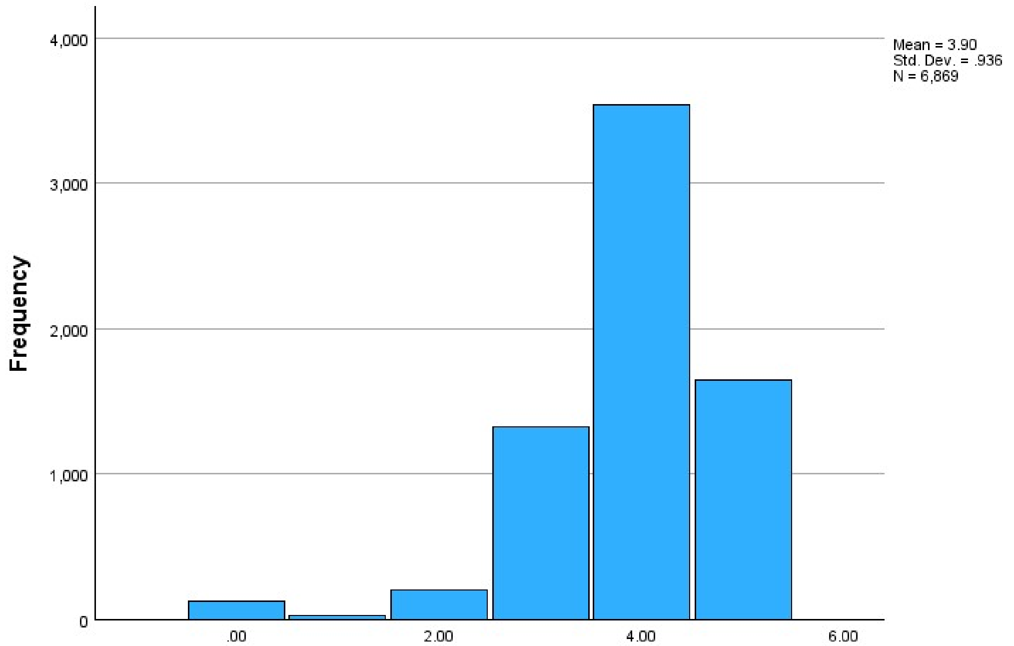
Statement 2: I find travelling by car relaxing



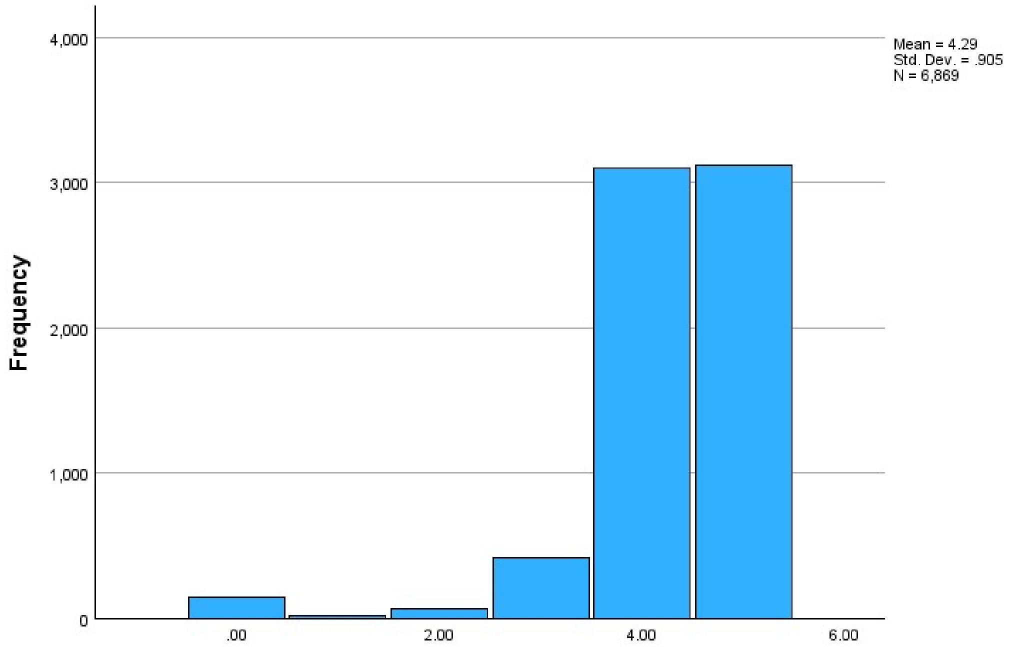
Statement 3: Travelling by car saves me time



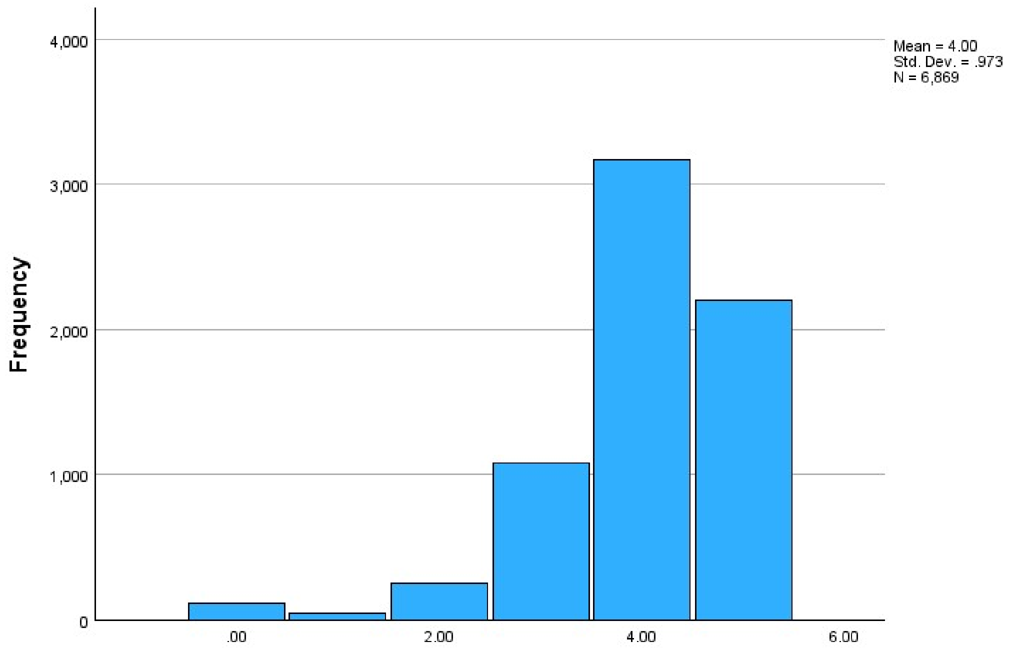
Statement 4: Travelling by car is safe



Statement 5: I find travelling by car flexible



Statement 6: Travelling by car is pleasant



Appendix E: Correlations attitude and SD

		Correlation	Significant (p-value)
Gender (reference = male)		-0.063	0.000
Age (reference = 12 - 29)	30 to 49	0.066	0.000
	50+	-0.086	0.000
License ownership		0.204	0.000
Primary occupation (reference = other)	Working	0.149	0.000
	Student	0.004	0.723
	Retired	-0.106	0.000
Education level	Medium	0.060	0.000
	High	0.040	0.001
Household income		0.132	0.000
Urbanity (rural is higher)		0.093	0.000
Number of persons in household		0.132	0.000