E-bike user groups and substitution effects
evidence from longitudinal travel data in the Netherlands

de Haas, Mathijs; Kroesen, Maarten; Chorus, Caspar; Hoogendoorn-Lanser, Sascha; Hoogendoorn, Serge

DOI
10.1007/s11116-021-10195-3

Publication date
2021

Document Version
Final published version

Published in
Transportation

Citation (APA)
de Haas, M., Kroesen, M., Chorus, C., Hoogendoorn-Lanser, S., & Hoogendoorn, S. (2021). E-bike user groups and substitution effects: evidence from longitudinal travel data in the Netherlands. *Transportation*, *49*(3), 815-840. https://doi.org/10.1007/s11116-021-10195-3

Transportation
https://doi.org/10.1007/s11116-021-10195-3

E-bike user groups and substitution effects: evidence from longitudinal travel data in the Netherlands

Mathijs de Haas[1] · Maarten Kroesen[2] · Caspar Chorus[2] · Sascha Hoogendoorn-Lanser[3] · Serge Hoogendoorn[4]

Accepted: 26 April 2021

Abstract
In recent years, the e-bike has become increasingly popular in many European countries. With higher speeds and less effort needed, the e-bike is a promising mode of transport to many, and it is considered a good alternative for certain car trips by policy-makers and planners. A major limitation of many studies that investigate such substitution effects of the e-bike, is their reliance on cross-sectional data which do not allow an assessment of within-person travel mode changes. As a consequence, there is currently no consensus about the e-bike's potential to replace car trips. Furthermore, there has been little research focusing on heterogeneity among e-bike users. In this respect, it is likely that different groups exist that use the e-bike for different reasons (e.g. leisure vs commute travel), something which will also influence possible substitution patterns. This paper contributes to the literature in two ways: (1) it presents a statistical analysis to assess the extent to which e-bike trips are substituting trips by other travel modes based on longitudinal data; (2) it reveals different user groups among the e-bike population. A Random Intercept Cross-Lagged Panel Model is estimated using five waves of data from the Netherlands Mobility Panel. Furthermore, a Latent Class Analysis is performed using data from the Dutch national travel survey. Results show that, when using longitudinal data, the substitution effects between e-bike and the competing travel modes of car and public transport are not as significant as reported in earlier research. In general, e-bike trips only significantly reduce conventional bicycle trips in the Netherlands, which can be regarded an unwanted effect from a policy-viewpoint. For commuting, the e-bike also substitutes car trips. Furthermore, results show that there are five different user groups with their own distinct behaviour patterns and socio-demographic characteristics. They also show that groups that use the e-bike primarily for commuting or education are growing at a much higher rate than groups that mainly use the e-bike for leisure and shopping purposes.

Keywords E-bike · Latent class analysis · Substitution · Travel mode choice · Random Intercept Cross-Lagged Panel Model (RI-CLPM) · Netherlands Mobility Panel (MPN) · Dutch national travel survey (OViN)

✉ Mathijs de Haas
mathijsdehaas@gmail.com

Extended author information available on the last page of the article

Introduction

The e-bike is gaining popularity in many Asian and European countries in recent years. While total bicycle sales in the EU grew with only 0.4% between 2010 and 2016, e-bike sales saw a growth of 284% in the same period and now accounts for 8.1% of total bicycle sales (CONEBI 2017). Germany, The Netherlands, Belgium, France and Italy account for almost 80% of e-bike sales in the EU in 2016. Relatively speaking, the share of e-bike sales is the highest in The Netherlands. In 2018, with 40% of new bicycles sold being an e-bike, more e-bikes were sold than conventional city bikes in the Netherlands (Stichting BOVAG-RAI Mobiliteit 2019).

When the e-bike was introduced in the Netherlands, the main adopters turned out to be older people, who primarily used the e-bike for leisure trips (Hendriksen et al. 2008). However, in recent years a shift can be observed based on data from the Dutch national travel survey (Statistics Netherlands 2013–2017). While in 2013 54% of e-bike kilometres were travelled by people of 65 years and older, in 2017 this share decreased to 46%. This indicates that also younger age groups are adopting the e-bike. It may be expected that these groups will use the e-bike differently. Indeed, this is reflected in a shift in trip purposes. In 2013 18% of e-bike kilometres were work related, whereas in 2017 this share increased to 23%. In 2017, 13% of all bicycle trips and 18% of the bicycle distance were travelled with an e-bike.

In the Netherlands, 50% of all car trips are under 7.5 km and 67% are under 15 km (Statistics Netherlands 2013–2017). As the e-bike allows travelling at greater speeds with less effort compared to a conventional bicycle, it has the potential to replace a substantial part of these car trips. As an e-bike emits 40 times less carbon dioxide (Shao et al. 2012) compared to a car, a substitution of car trips with e-bike would benefit the environment, as well as helping reduce road congestion. However, whether the e-bike brings environmental and other benefits depends on the mode it is replacing (Cherry and Cervero 2007). If the e-bike is mainly substituting non-motorized modes such as the conventional bicycle and walking, benefits could even be negative.

Several studies have already focused on the effect that the advent of the e-bike has on travel behaviour. These studies generally report that the e-bike substitutes not only the conventional bicycle, but also, to a certain degree, the car and public transport, depending on local context. For instance, two studies with a geographic focus on China show that in areas with a high quality public transport network, the e-bike is seen as an affordable alternative to public transport (Cherry and Cervero 2007), whereas in areas without sufficient public transport facilities the e-bike mainly substitutes the conventional bicycle (Weinert et al. 2007b). A limitation of previous studies is, however, that they are either based on a cross-sectional survey or in-depth interviews which only allow for comparisons between individuals (differences in travel mode choices) and do not allow an evaluation of within-person effects (changes in travel mode choices) over time. As such, the current state of the art of the literature into e-bike substitution effects provides an incomplete picture, hampering the derivation of sound policies in this regard.

The contribution of this study to the literature is twofold. The first aim is to assess whether substitution effects of the e-bike can be observed at an individual level; that is, we study whether the advent of the e-bike has led to actual changes in travel mode choices. To do so, longitudinal data from the Netherlands Mobility Panel (MPN) is used, which—in contrast to cross-sectional data—allows for such analyses. Note that the Netherlands Mobility Panel is representative for the Dutch population and includes both e-bike owners and non-e-bike owners.

The second goal of this study is to assess trends in the population of e-bike users, with a particular focus on heterogeneity in user-groups and their e-bike behaviours. Although a shift in the use of e-bike can be observed in terms of age and trip purpose, little is known about the heterogeneity among e-bike users in terms of their usage patterns. It is likely that different groups exist that use the e-bike for different reasons and in different ways. By considering different types of e-bike users in terms of their socio-demographic characteristics as well as their usage patterns, it can be assessed whether it is likely that any substitution effects might change in the future. We use 5 years of data (2013–2017) of the Dutch national travel survey (Statistics Netherlands 2013–2017) to reveal different e-bike user groups and assess how these groups developed over the years.

The remainder of this paper is structured as follows. First, a brief overview of relevant studies regarding the effects of the e-bike on travel behaviour is provided. The next section shows how e-bike trips substitute trips with other modes. In the following section, we discuss the different e-bike user groups and their development over the years. The final section presents conclusions and recommendations for future research.

Background literature

Together with the increase in popularity of the e-bike, more studies on substitution effects of e-bikes are emerging. What modes of transport the e-bike is replacing differs greatly between areas. Several studies in Asia, where the e-bike was adopted first, focus on China. This may be explained by the popularity of the e-bike in China in comparison with other Asian countries. One reason for the uptake of the e-bike in China were local government policies. In the late 1990s several major Chinese cities banned the sale of gasoline-powered scooters which was one of the most competitive modes to the e-bike (Weinert et al. 2007a). Several studies in China found that people (inhabitants of the cities Kunming, Shanghai and Jinan) would use the bus if they would not own an e-bike, suggesting the e-bike is seen as an affordable, higher quality mobility alternative to public transport (Cherry and Cervero 2007; Cherry et al. 2016; Montgomery 2010). Another study in Asia focusing on the Chinese city Shijiazhuang, however, found that most e-bike users considered the conventional bicycle as the next best alternative to e-bike (Weinert et al. 2007b). The authors of the latter study hypothesize that these differences might be explained by the differences in quality of the bus service and the city size differences, as Shijiazhuang is smaller, resulting in shorter trip distances. For studies that focus on Asian countries, it should be noted that electrical scooters (without pedal assistance) are also considered e-bikes. In the present study, only pedal-assisted electrical bicycles are considered e-bikes.

In studies that focused on areas outside Asia, it was found that people mainly bought an e-bike to replace (some of) their car trips. This was for instance concluded from a study that focused on Australia (Johnson and Rose 2013) and North America (MacArthur et al. 2014, 2018). In Sweden, Hiselius and Svensson (2017) found, based on a relatively small survey among e-bike users, that the car is the main mode that is replaced by e-bike and that in urban areas more people replace the conventional bicycle by e-bike compared to rural areas. Jones et al. (2016) concluded, based on a small sample of English and Dutch e-bike owners, that the e-bike was primarily bought to replace a conventional bicycle, but that both conventional bicycle and car use decreased after the purchase.

Kroesen (2017) studied effects of e-bike ownership on various indicators of travel behaviour. Data from the Dutch national travel survey was used to assess whether e-bike substitutes other modes of transport. It was shown that e-bike use not only has significant effects on conventional bicycle, car and public transport use but also has a substantial generative effect on the total distance travelled. However, since cross-sectional data was used for this study, causal directions (for instance from vehicle ownership to mode use) had to be assumed rather than being derived from the data.

From previous studies it seems that the local context is an important factor in the effects that the e-bike has on travel behaviour. As previous findings show that the e-bike mainly replaces public transport in areas with a high-quality public transport network and mainly the car in more car-oriented areas, this may have implications for the present study. As the focus is on the Netherlands, it should be noted that in the Netherlands people travel mostly by car or bicycle. Approximately 29% of trips are travelled by car as a driver and 26% by bicycle (either conventional or electric) (Kennisinstituut voor Mobiliteitsbeleid 2019). It can therefore be expected based on earlier studies, that mainly the car or the conventional bicycle will be substituted by the e-bike in the Netherlands.

Other Dutch local context that is relevant for this study is the fact that bicycle ownership is very high. There are more bicycles than inhabitants in the Netherlands (Fietsersbond 2019). While there are some local e-bike sharing systems, the e-bike sharing market in the Netherlands is very small in comparison with total e-bike use. Furthermore, until 2020, there were no national policies to promote the use and ownership of the e-bike specifically. In 2020 a new tax scheme was introduced, enabling companies to provide their employees an e-bike with limited costs for the employee. Since this policy was introduced after the last wave of data collection that was used in this study (see "data" section below) we assume that it did not affect the results.

One recent study by Sun et al. (2020) studied effects of acquiring an e-bike on travel behaviour based on 4 years of panel data from the Netherlands Mobility Panel. Results showed that the year after acquiring an e-bike, conventional bicycle use reduced significantly as well as car, walking and public transport use, but to a smaller extent. While these results are in line with Kroesen (2017), they only reflect short-term effects. Therefore, the main contribution of the present study is that it shows yearly effects of using an e-bike on the use of other transport modes. In addition, to assess whether it is likely that substitution effects will change in the future, trends in different user groups of the e-bike are analysed.

Assessing substitution effects of the e-bike and trends in the different user groups can be regarded as two different studies, as both analyses have their own method, data and results. For readability reasons, the method, data and results of the analysis of substitution effects (study 1) will be discussed first, followed by the same sections for the analysis of trends in user groups (study 2).

Study 1: Substitution effects of the e-bike

In this section, substitution effects of e-bike use are assessed. First, we present the methodology followed by results.

Methods

Here, we briefly describe the various elements of the methodology proposed to study the hypothesised substitution effects.

Model conceptualisation

In this study, it will be assessed how the use of different travel modes influences the use of other travel modes over time. By studying these effects over time, it can be assessed whether e-bike substitutes and/or complements travel by other modes. Similar to Golob and Meurs (1987), we study possible substitution effects by looking at trip rates with different travel modes over time. As the e-bike is in theory a travel mode that is not only suited to replace conventional bicycle trips, but also car or public transport, trip rates with the most important travel modes in the Netherlands (car, train, BTM (bus, tram or metro), bicycle, e-bike and walking) are considered in the present study.

To analyse the effects of mode use over time, a Cross-Lagged Panel Model (CLPM) will be used. A CLPM is a structural equation model (SEM) that allows examining (causal) relationships between variables that are measured at two or more moments in time. There is, however, an important limitation of the traditional CLPM. In a traditional CLPM, the stability of constructs is controlled for by including autoregressive relationships. After controlling for stability, the cross-lagged relationships are assumed to be a correct representation of causal influences and a CLPM is often used to show which of the variables is causally dominant. However, Hamaker et al. (2015) showed that when the stability of the constructs is to some extent of a trait-like, time-invariant nature, the autoregressive parameters are not able to correctly control for this. In other words, the traditional CLPM is not able to fully account for time-invariant between-person differences. As a result, the model is not able to isolate within-person changes. Hamaker et al. (2015) found that this could, in some cases, result in drawing wrong conclusions about the presence of causal relationships, the causal dominance of constructs or about the sign of causal relationships.

To cope with this limitation, Hamaker et al. (2015) present an alternative to the traditional CLPM, the Random Intercept Cross-Lagged Panel Model (RI-CLPM). In this approach, to correct for time-invariant between-person differences, the variance of the observed indicators is split into a between-person level random intercept that represents the individual's trait-like deviation from the means and within-person level temporal deviations from their expected scores (the mean plus the random intercept).

Figure 1 shows the conceptual model of the RI-CLPM. For clarity of communication, only two observed indicators are shown in the figure. In the full model, six indicators are included (car, train, BTM, bicycle, e-bike and walking). The random intercepts are latent variables with their factor loadings constrained to 1. In contrast to a regular CLPM, the autoregressive parameters (α, α_2, δ and δ_2) do not represent rank-order stability of individuals, but a within-person carry-over effect (Hamaker et al. 2015). In other words, a positive parameter implies that when an individual makes more trips with a certain mode than expected based on the temporal group mean and the random intercept, he or she is likely to also make more trips than expected in a following year. The cross-lagged parameters (β and γ) indicate the within-person effect of the use of a certain travel mode on the use of other modes in the following year.

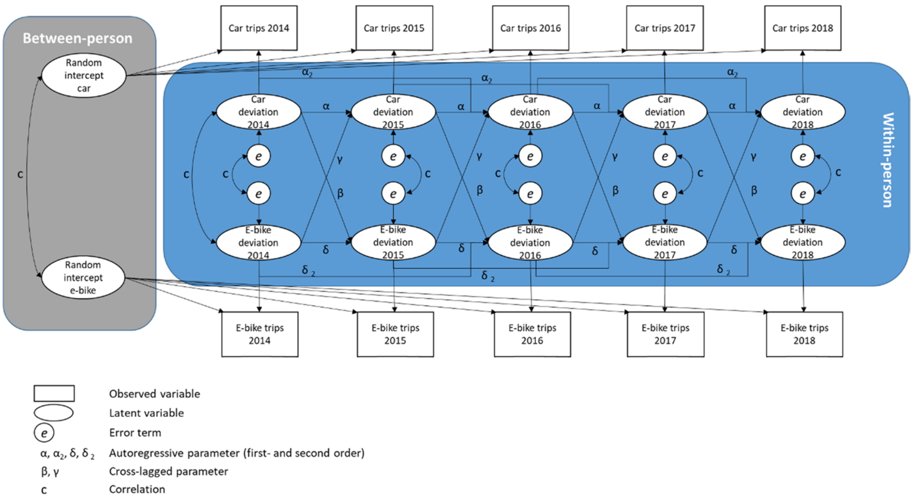

Fig. 1 Partial conceptual model of the Random Intercept Cross-Lagged Panel Model; the figure shows a five-wave, two-variable model for clarity of communication. The full model includes six indicators (car, train, BTM, bicycle, e-bike and walking)

Data

To estimate the RI-CLPM, longitudinal data are required. In the present study, panel data from the Netherlands Mobility Panel (MPN) are used. The MPN is an annual household panel that started in 2013 and consists of approximately 2000 complete households. Each year, household members of at least 12 years old are asked to complete a 3-day travel diary

Table 1 Participation patterns of the MPN, wave 1 through 6 (2013–2018) (n = 12,215)

Pattern	#	%	Pattern	#	%	Pattern	#	%	Pattern	#	%
000001	1100	9.0	010001	25	0.2	100001	12	0.1	110010	5	0.0
000010	615	5.0	010010	4	0.0	100011	5	0.0	110011	18	0.1
000011	1813	14.8	010011	9	0.1	100100	22	0.2	110100	84	0.7
000100	394	3.2	010100	153	1.3	100101	10	0.1	110101	18	0.1
000101	154	1.3	010101	29	0.2	100110	3	0.0	110110	30	0.2
000110	164	1.3	010110	15	0.1	100111	8	0.1	110111	102	0.8
000111	643	5.3	010111	79	0.6	101000	156	1.3	111000	355	2.9
001000	142	1.2	011000	453	3.7	101001	6	0.0	111001	23	0.2
001001	12	0.1	011001	37	0.3	101010	5	0.0	111010	39	0.3
001010	1	0.0	011010	32	0.3	101011	9	0.1	111011	115	0.9
001011	10	0.1	011011	73	0.6	101100	40	0.3	111100	149	1.2
001100	63	0.5	011100	195	1.6	101101	25	0.2	111101	125	1.0
001101	27	0.2	011101	170	1.4	101110	17	0.1	111110	115	0.9
001110	13	0.1	011110	79	0.6	101111	77	0.6	111111	858	7.0
001111	55	0.5	011111	443	3.6	110000	492	4.0			
010000	1217	10.0	100000	1063	8.7	110001	10	0.1	Total	12,215	100.0

and fill in an extensive questionnaire that includes questions on topics such as occupational status, use of different modes of transport and life events in the past year. Furthermore, every household is asked to fill in a questionnaire about household related characteristics, such as information about household composition and ownership of means of transport. More information about the MPN can be found in Hoogendoorn-Lanser et al. (2015). Currently, data from the first six waves (2013–2018) are available. However, the first wave of the MPN is not used in the analyses as including this wave led to estimation problems. This will be discussed in detail in section "Model estimation" below.

To account for panel attrition (respondents dropping out of the panel between waves), new respondents are recruited yearly. Table 1 shows the number of respondents and their response patterns for the first through the sixth wave (e.g. pattern 000001 indicates a respondent that only participated in wave 6, while pattern 111111 represents respondents that participated in wave 1 through 6). Since the first wave of MPN is not used, all respondents of the second through sixth wave that participated in at least one wave are included in the analysis, 11,152 in total. In the ensuing, it is explained how missing data is handled.

Mode use is included in the model as the trip rates per mode of transport in 3 days. These trip rates are reported in the travel diary that respondents of the MPN complete every year for the same 3 days. As indicated in the previous section, six modes of transport are included in the model, which are car (as driver), train, BTM, bicycle, e-bike and

Table 2 Sample composition MPN wave 2 through 6 (2014–2018) (n = 11,152)

Variable		
Car (as driver) trip rate (over 3 days)	Mean (SD)	3.00 (3.91)
Train trip rate (over 3 days)	Mean (SD)	0.26 (0.92)
BTM trip rate (over 3 days)	Mean (SD)	0.20 (0.80)
Bicycle trip rate (over 3 days)	Mean (SD)	1.88 (3.10)
E-bike trip rate (over 3 days)	Mean (SD)	0.40 (1.57)
Walking trip rate (over 3 days)	Mean (SD)	1.24 (2.39)
Gender	Male	46%
	Female	54%
Age	Mean (SD)	44.5 (19.0)
Educational level	Low	35%
	Mid	37%
	High	28%
Occupational status	Employed	54%
	Unemployed	10%
	Incapacitated	5%
	Student	16%
	Retired	16%
Personal net income per month	No income	26%
	Less than €1500	34%
	€1500–€2500	29%
	More than €2500	13%
Car ownership		68%
Bicycle ownership		70%
E-bike ownership		17%

walking. If a multi-modal trip is reported, only the main mode of transport is considered. As travel times and distances of individual trip legs are unknown in the MPN, assumptions have to be made to determine the main mode of transport. If a multi-modal trip is reported, the first mode on the following list is considered the main mode: train, BTM, car, e-bike, bicycle, walking. Table 2 shows the sample composition. In this table, only data from the most recent wave of a respondent are used, since some variables are time-variant. The sample composition is fairly representative of the Dutch population. It can be seen that just over one in six (17%) respondents owns an e-bike, while 70% owns a conventional bicycle. It should be noted that a considerable amount (37%) of e-bike owners also owns a conventional bicycle.

Model estimation

To estimate the RI-CLPM, the R package lavaan is used (Rosseel 2012). Since all respondents that participated at least 1 year are included in the analysis, the model has to handle missing data. To this end, the model is estimated using Full Information Maximum Likelihood (FIML), which has been shown to effectively handle missing data by Enders and Bandalos (2001). Furthermore, to increase precision of the parameter estimates and ease interpretation, all autoregressive and cross-lagged parameters and within-wave correlations are constrained to be equal across waves. As it is expected that possible substitution effects may be different between trip purposes, four models are estimated; a general model without distinction between trip purposes and three models specifically for commuting-, leisure- and shopping trips. For the model with commuting trips, including all six waves of the MPN data results in estimation problems. It is expected that these problems are caused by having too few respondents who use an e-bike for commuting and participated in both the first and second wave as removing the first wave of data solves these problems. In order to use the same data for the different models, all models are estimated using the second through sixth wave of the MPN.

Results

Here, we discuss the key results of the four estimated models. First, we discuss the results of the model without distinction between trip purposes, followed by a discussion of substitution effects specifically for commuting, leisure of shopping trips.

Substitution effects without distinction between trip purposes

Table 3 shows the regression parameters of the RI-CLPM with all trips included. The model has a *Comparative Fit Index* (CFI) of 0.983, a *Root Mean Square Error of Approximation* (RMSEA) of 0.013 and a *Standardized Root Mean Square Residual* (SRMR) of 0.027. All these values suggest a good model fit (Brown 2014). As discussed in the paragraph "Model conceptualisation", in contrary to a regular CLPM, the autoregressive parameters do not represent rank-order stability of individuals, but a within-person carry-over effect (Hamaker et al. 2015).

All first-order autoregressive parameters are positive and significant, indicating that when an individual uses a certain mode at time *t-1* more than would be expected based on the mean and random intercept, it is likely that this individual will also show a higher use of this mode on time *t* and vice versa. For the second-order parameters the same

Table 3 Regression parameters of the RI-CLPM, no distinction between trip purposes (MPN 2014–2018)

	Effect on					
	Car as driver	Train	BTM	Bicycle	E-bike	Walk
Autoregression (first-order)	**0.199 (0.000)**	**0.243 (0.000)**	**0.196 (0.000)**	**0.221 (0.000)**	**0.344 (0.000)**	**0.347 (0.000)**
Autoregression (second-order)	**0.115 (0.000)**	**0.074 (0.000)**	0.013 (0.553)	**0.095 (0.000)**	**0.200 (0.000)**	**0.186 (0.000)**
Car as driver (t-1)		– 0.006 (0.051)	0.000 (0.930)	– 0.083 (0.064)	– 0.007 (0.367)	0.011 (0.211)
Train (t-1)	0.020 (0.692)		– 0.000 (0.977)	**– 0.023 (0.024)**	0.010 (0.684)	0.035 (0.292)
BTM (t-1)	– 0.034 (0.565)	0.002 (0.889)		**– 0.097 (0.014)**	0.008 (0.146)	– 0.031 (0.430)
Bicycle (t-1)	**– 0.035 (0.040)**	– 0.001 (0.868)	– 0.000 (0.950)		– 0.000 (0.990)	– 0.010 (0.392)
E-bike (t-1)	– 0.012 (0.675)	– 0.000 (0.993)	0.001 (0.922)	**– 0.092 (0.000)**		0.011 (0.528)
Walk (t-1)	**0.046 (0.017)**	0.005 (0.267)	– 0.001 (0.822)	0.001 (0.932)	– 0.000 (0.970)	

p values are presented in parentheses, parameters with $p < 0.05$ are bold interpretation holds, except that they show the effect of the use at time *t-2* on the use on time *t*. As the interest in this study is on the cross-lagged parameters, the autoregressive parameters will not be discussed in the following models.

From the cross-lagged parameters it can be seen that the e-bike only has a significant substitution effect on the conventional bicycle. This result contrasts results obtained in previous studies, as they often conclude that the e-bike not only substitute the conventional bicycle but also the car and public transport [e.g. Jones et al. (2016) and Kroesen (2017)].

Besides this effect of the e-bike on the conventional bicycle, there are some other significant effects. Both the train and BTM appear to be substitutes of the conventional bicycle. Regarding the train mode, this is somewhat unexpected, as in the Netherlands the train is often used for longer distances than the bicycle. Furthermore, we find that an increase in bicycle use leads to a decrease in car use. Finally, an increase in walking trips leads to a small increase in car trips, an effect that is difficult to explain.

Substitution effects for commuting trips

To study the substitution effects specifically for commuting trips, only commuting trips of employed respondents are used in the model estimation. This reduces the sample size to 6009 respondents. Furthermore, BTM is not included as it turned out there were too few commuting trips by BTM in the MPN. This is partly caused by the bus, tram and metro mainly being used as access- and egress-modes, while only the main mode of transport is considered in the model. This model also shows a good model fit with a CFI of 0.955, a RMSEA of 0.024 and a SRMR of 0.043. The regression parameters of the RI-CLPM with only commuting trips are shown in Table 4.

Interestingly, the results show that specifically for commuting trips, the e-bike not only substitutes the conventional bicycle, but also the car. Apparently, for commuting trips people consider the e-bike not only as a replacement for the conventional bicycle but also for the car. Furthermore, for commuting, the car acts as a substitute for the train, while the conventional bicycle stimulates walking and walking stimulates train use.

Substitution effects for leisure trips

To model the substitution effects specifically for leisure trips, all respondents are included. Again, this model shows a good model fit with a CFI of 0.952, a RMSEA of 0.016 and a SRMR of 0.030. Table 5 shows the regression parameters of this RI-CLPM.

For leisure trips it turns out that the e-bike only substitutes the conventional bicycle as this is the only significant parameter estimate of e-bike trips at $t-1$. The use of BTM stimulates e-bike use. Furthermore, there are substitution effects of the car on the conventional bicycle and BTM on walking. Just as in the general model, there is a positive effect of walking on car use. For leisure trips, a possible explanation might be found in the fact that walking for leisure purposes often consists of walking as the activity, without a specific destination (e.g. walking in a forest). It is possible that people would like to make a walking tour in different areas, for which they need a car to reach these areas.

Table 4 Regression parameters of the RI-CLPM, only commuting trips (MPN 2014–2018, n = 6.009)

	Effect on				
	Car as driver	Train	Bicycle	E-bike	Walk
Autoregression (first-order)	**0.269 (0.000)**	**0.281 (0.000)**	**0.208 (0.000)**	**0.389 (0.000)**	**0.481 (0.000)**
Autoregression (second-order)	**0.060 (0.024)**	**0.053 (0.036)**	0.034 (0.125)	**0.263 (0.000)**	**0.205 (0.000)**
Car as driver (t-1)		**– 0.020 (0.003)**	– 0.016 (0.171)	– 0.007 (0.398)	– 0.004 (0.479)
Train (t-1)	– 0.068 (0.148)		– 0.028 (0.347)	– 0.005 (0.333)	0.004 (0.764)
Bicycle (t-1)	– 0.006 (0.835)	– 0.018 (0.067)		– 0.019 (0.197)	**0.017 (0.045)**
E-bike (t-1)	**– 0.102 (0.017)**	– 0.005 (0.760)	**– 0.056 (0.047)**		0.003 (0.797)
Walk (t-1)	– 0.083 (0.146)	**0.045 (0.030)**	– 0.012 (0.742)	0.010 (0.508)	

p values are presented in parentheses, parameters with $p < 0.05$ are bold

Table 5 Regression parameters of the RI-CLPM, only leisure trips (MPN 2014–2018)

	Effect on					
	Car as driver	Train	BTM	Bicycle	E-bike	Walk
Autoregression (first-order)	**0.059 (0.001)**	0.009 (0.566)	**0.052 (0.002)**	**0.089 (0.000)**	**0.313 (0.000)**	**0.329 (0.000)**
Autoregression (second-order)	0.025 (0.182)	**– 0.045 (0.010)**	– 0.018 (0.308)	**0.061 (0.000)**	**0.176 (0.000)**	**0.157 (0.000)**
Car as driver (t-1)		– 0.005 (0.039)	0.004 (0.134)	**– 0.122 (0.007)**	0.011 (0.101)	0.022 (0.058)
Train (t-1)	0.018 (0.724)		0.011 (0.281)	0.014 (0.138)	– 0.026 (0.255)	0.008 (0.871)
BTM (t-1)	**0.125 (0.024)**	0.006 (0.587)		– 0.004 (0.925)	**0.011 (0.033)**	**– 0.120 (0.025)**
Bicycle (t-1)	0.010 (0.520)	0.001 (0.862)	– 0.006 (0.063)		0.008 (0.706)	0.000 (0.976)
E-bike (t-1)	0.031 (0.232)	– 0.005 (0.403)	– 0.006 (0.256)	**– 0.045 (0.033)**		0.038 (0.120)
Walk (t-1)	**0.037 (0.006)**	0.002 (0.596)	– 0.001 (0.585)	0.006 (0.602)	0.007 (0.161)	

p values are presented in parentheses, parameters with $p < 0.05$ are bold

Table 6 Regression parameters of the RI-CLPM, only shopping trips (MPN 2014–2018)4

	Effect on					
	Car as driver	Train	BTM	Bicycle	E-bike	Walk
Autoregression (first-order)	**0.140 (0.000)**	**– 0.112 (0.000)**	– 0.030 (0.062)	**0.118 (0.000)**	**0.182 (0.000)**	**0.181 (0.000)**
Autoregression (second-order)	**0.124 (0.000)**	**– 0.108 (0.000)**	**– 0.040 (0.018)**	**0.068 (0.000)**	**0.133 (0.000)**	**0.107 (0.000)**
Car as driver (t-1)		0.001 (0.480)	– 0.001 (0.734)	0.020 (0.714)	– 0.013 (0.088)	– 0.003 (0.755)
Train (t-1)	– 0.051 (0.556)		0.022 (0.160)	0.015 (0.170)	0.018 (0.590)	**0.282 (0.000)**
BTM (t-1)	– 0.071 (0.254)	– 0.004 (0.528)		**– 0.166 (0.027)**	– 0.002 (0.784)	– 0.053 (0.282)
Bicycle (t-1)	0.014 (0.297)	0.001 (0.430)	0.002 (0.361)		0.039 (0.405)	– 0.015 (0.151)
E-bike (t-1)	– 0.035 (0.120)	0.001 (0.822)	0.004 (0.335)	**– 0.075 (0.000)**		0.002 (0.891)
Walk (t-1)	0.005 (0.754)	0.003 (0.047)	– 0.004 (0.119)	– 0.012 (0.380)	**– 0.021 (0.010)**	

p values are presented in parentheses, parameters with $p < 0.05$ are bold

Substitution effects for shopping trips

Table 6 shows the regression parameters of the final RI-CLPM with only shopping trips included. The CFI of this model is just under the limit value of 0.95 to be considered as good model fit. However, with a CFI of 0.934 it can still be considered acceptable (Brown 2014). The RMSEA and SRMR can both be considered as an indication of a good model fit with values of respectively 0.019 and 0.035.

There are only a few significant effects for shopping trips. Again, for the e-bike it can be seen that it only substitutes the conventional bicycle. Furthermore, walking substitutes the e-bike to a certain extent and BTM substitutes the conventional bicycle. Lastly, train use has a positive effect on the number of walking trips.

Conclusion substitution effects

The analyses into substitution effects of e-bike use showed that at a general level—that is, taking all trip purposes together—e-bike trips only substitute conventional bicycle trips. Only for commuting trips it was found that e-bike trips, in addition to substituting conventional bicycle trips, also substitute trips made by car. This implies that if the share of commuting in e-bike use would increase, this substitution effect will probably also be observed at the general level in due time. To assess whether it is likely that substitution effects will indeed change in the future, it is important to know which different e-bike user groups exist and how these groups are growing or shrinking over the years as a share of the total population of travellers. This is assessed in the next section.

Study 2: E-bike user groups

The previous section showed that it is important to know which different e-bike user groups exist and how these groups are growing or shrinking over the years. In this section, we present a statistical analysis to reveal the different user groups.

Methods

Here, we briefly describe the various elements of the methodology proposed to study the different e-bike user groups.

Model conceptualisation

To reveal the different e-bike user groups, a latent class analysis (LCA) will be used. The idea behind LCA is that observed associations between different indicators are explained by an underlying latent variable (McCutcheon 1987). The latent variable is not directly measured, but is inferred from observed indicators. Crucially, LCA differs from conventional segmentation analysis by letting the classes emerge from correlations in the data, as opposed to being a priori imposed by the researcher. An important difference between LCA and standard cluster analysis is that LCA is a model-based clustering approach in which objects are probabilistically assigned to classes (Vermunt and Magidson 2002).

E-bike user groups can be defined in different ways. One could cluster the e-bike users based on how they use the e-bike (for instance trip rates with the e-bike for different purposes) or based on sociodemographic variables. In this study the user groups will be defined using socio-demographic variables, while the trip frequencies of e-bike for various purposes are included as (inactive) covariates of the model. This is because the behavioural variables (trip rates for different purposes) are more volatile and therefore subject to random fluctuations (e.g. a person may not use the e-bike on a particular day for a trivial reason, such as having a day off from work or having no out-of-home activities). In our case, strong fluctuations are especially likely since we rely on data from the Dutch national travel survey which only measures the travel behaviour of respondents for a single particular day. The socio-demographic variables, on the other hand, can provide a stable picture of the various e-bike user groups and are informative on how people *generally* use the e-bike. For example, it may be expected that the typical old-age retired e-bike user will use the e-bike mostly for recreational purposes (and therefore it is not expected to substitute trips by car) while a middle-aged employed individual may be expected to use the e-bike for commuting trips (which may previously have been made by car). Figure 2 shows the conceptual model for the latent class analysis. To cluster e-bike users, five sociodemographic variables (gender, age, education level, work status and household composition) are used as indicators.

Latent class analysis allows for the use of covariates. Covariates are exogenous variables that are used to predict class membership (Vermunt and Magidson 2002). In this study, the survey year is included as an exogenous variable. As already discussed, the share of people of 65 years and older in terms of travelled e-bike kilometres has decreased in recent years. This implies that the user group is changing over time. As the interest is on assessing how the different user groups have grown over the years, the survey year is included as a covariate.

To have an indication of e-bike use per user group, so-called inactive covariates, reflecting the reported e-bike trip rates for various purposes on the reporting day, are added to the model. Inactive covariates do not influence the model in any way and are merely used to describe the different groups.

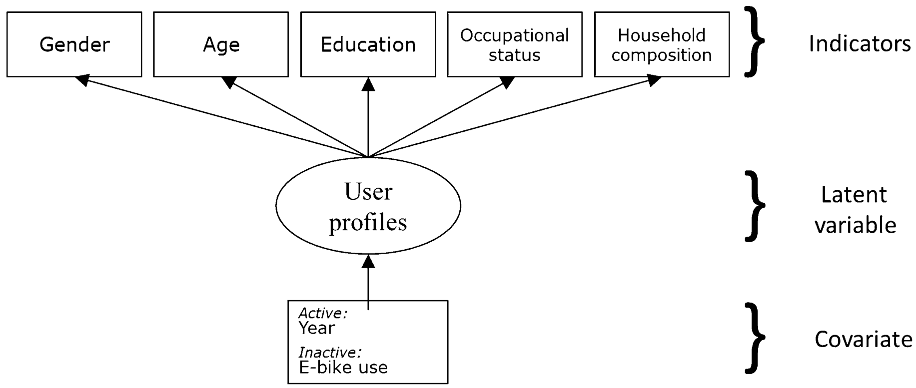

Fig. 2 Conceptual model of the latent class analysis

Data

To estimate the LCA, data from the Dutch national travel survey OViN (in Dutch: Onderzoek Verplaatsingen in Nederland) are used (Statistics Netherlands 2013–2017). The Dutch national travel survey is a cross-sectional travel survey in which participants are asked to record all the trips they made for a single, predefined day. Compared to the MPN, which was used to study substitution effects, the national travel survey is larger in terms of number of respondents. Between 37,000 and 43,000 respondents participate yearly. In addition, because of its (repeated) cross-sectional nature, it is better suited than a mobility panel to study the changing composition of e-bike users over time. Whereas a mobility panel (like the MPN) is (by definition) affected by a cohort effect (for one, members in a panel get older over time), a repeated cross-sectional survey is not affected by such biases. Hence, each survey provides a 'fresh' snapshot view of the different e-bike groups and their respective sizes The respondents participating in the national travel survey are randomly drawn from the Dutch Personal Records Database (in Dutch: Basisregistratie Personen (BRP), which contains information on all Dutch residents), resulting in a representative sample of the Dutch population.

Besides keeping a 1-day travel diary, a short questionnaire is included to gather some information on the personal- and household level, such as household composition and ownership of means of transport. Starting from 2013, the e-bike was included in the national travel survey. From this moment respondents were able to report the ownership and use of the e-bike. Before 2013, no distinction was made between the conventional bicycle and the e-bike.

The present study uses data from 2013 to 2017. In 2018 the set-up of the Dutch national travel survey changed and e-bike ownership is no longer measured on an individual level. Therefore, data from 2018 onwards cannot be used in this study. As the goal is to reveal different e-bike user groups, only respondents that own an e-bike are used in the analysis. Between 8.1 and 13.9% of respondents own an e-bike. The effective sample sizes are as follows: 3413, 4170, 4014, 4404 and 5129 for the years 2013 through 2017 respectively. This results in a total sample size of 21,130 respondents.

Model estimation

To estimate the LCA, the statistical software package Latent Gold is used (Vermunt and Magidson 2005). To decide on the number of classes, two methods are used, as described by Magidson and Vermunt (2004). The first method uses the Bayesian Information Criterion (BIC). The BIC takes model fit and parsimony into account. A model with a lower BIC is preferred over a model with a higher BIC. The second methods uses the L^2 of the 1-class model as a baseline measure of the total amount of association within the data. When the L^2 of a model with more classes is compared to the L^2 of the 1-class model, the reduction in L^2 represents the additional explained association. When the reduction in L^2 becomes relatively low, it is no longer justified to add an extra class to the model.

Results

Here, we discuss the key results of latent class analysis and discuss the trends in e-bike user groups.

E-bike user groups

As described in the section "Model estimation", the BIC and reduction of L^2 are used to decide on the appropriate number of clusters in the LCA. A 1-class to 10-class model is estimated without any covariates to assess only the variance between the indicators. The BIC value suggests that a model with a least 10 classes would be appropriate, as this model has the lowest BIC value. Since a model with such a high number of classes would be impossible to interpret meaningfully, we instead relied only on the relative reduction in L^2 as the criterion to decide on the optimal number of classes (Magidson and Vermunt 2004). With respect to this criterion, it was found that after the 5-class solution, the reduction of L^2 became small (less than 3%), suggesting that the 5-class model provides a good balance between model fit and model parsimony.

Table 7 shows the profiles of the five different classes from the final model. It should be noted that the class sizes indicate the average shares of the classes in the years 2013 through 2017. The shares per year are calculated in the next section. The table also shows the composition of the total e-bike user sample. From the composition of the total sample, the high share of women and retired people and the relatively high average age stand out. Apparently, the e-bike user group is still dominated by the initial adopters in the Netherlands; the older retired people (Hendriksen et al. 2008). In contrast with other studies, we find that the e-bike users in the Netherlands are predominantly female [see, e.g. MacArthur et al. (2018) and Wolf and Seebauer (2014)].

The first and largest class (53% of the sample) represents the retired older leisure users. This group is comprised of the traditional e-bike users, with virtually everyone in this group aged 65+. This group's average age is 72 years old. Consequently, nearly everyone in this group is retired. This user group primarily uses e-bikes for leisure or shopping purposes.

The second class (20% of the sample) represents the middle-aged full-time working people. These users are considerably younger than those in the first class, with an average age of around 53 years old. Most of the people in this group have full-time jobs (78%), which is also reflected in the relatively high share of work-related trips in this group.

The third class (14% of the sample) represents mostly female and relatively older leisure users. This third group consists primarily of women aged between 50 and 65 years old. This group consists almost equally of people with part-time jobs and people who are primarily homemakers. Similar to the first class, this group mainly uses e-bikes for leisure or shopping purposes.

The fourth class (11% of the sample) represents the younger part-time working women with children. This group is largely comprised of women. With an average age of 46 years old, this group is relatively young compared to the previous groups, with most of the people in this group having part-time jobs. Notably, over 80% of the people in this group reside in households consisting of two adults (partners) with children. This group uses e-bikes for work-related trips, as well as for leisure and shopping purposes.

The fifth and smallest class (1% of the sample) represents students and pupils. This group largely consists of teenagers: 94% of this group is aged 12 to 20 years old. Given this group's young average age, the group includes a high proportion of lower educated people. Moreover, 90% of the people in this group are high school or college students, which is also reflected in the fact that people in this group frequently use e-bikes for education-related purposes.

Table 7 Profiles of the 5-class Latent Class Model

	Class[a]	RO	MF	OF	YF	ST	Total
Indicators	Class size (%)	53	20	14	11	1	–
Gender (%) (Wald = 618, $p<0.00$)	Male	44	65	7	2	46	38
	Female	56	35	93	98	54	62
Age (Wald = 440, $p<0.00$)	12–21 years	0	0	0	0	94	1
	21–30 years	0	2	0	10	6	2
	31–40 years	0	8	0	19	0	4
	41–50 years	0	25	2	31	0	9
	51–64 years	4	65	98	40	0	34
	65 and older	96	0	0	0	0	51
	Mean	72.3	52.6	58.8	46.3	16.2	62.7
Educational level (%) (Wald = 1447, $p<0.00$)	Low	54	25	47	21	77	44
	Mid	26	39	36	48	20	32
	High	17	34	15	30	2	22
	Unknown	2	2	2	1	1	2
Occupational status (%) (Wald = 2465, $p<0.00$)	Works 12–30 h/week	1	4	38	57	3	13
	Works 30+ h/week	1	78	2	11	5	18
	Works in household	0	1	35	20	0	7
	Student	0	0	0	1	90	2
	Unemployed	0	4	5	2	1	2
	Incapacitated	0	10	10	5	0	4
	Retired	98	1	3	0	0	53
	Other	0	2	7	4	2	2
Household composition (%) (Wald = 2754, $p<0.00$)	Single	24	17	10	5	6	18
	Couple without children	73	44	82	9	0	60
	Couple with children	2	35	7	79	82	19
	Other	1	4	1	7	11	3
Active covariates							
Reporting year (%)	2013	18	13	18	14	14	16
	2014	21	18	21	18	16	20
	2015	18	20	21	19	18	19
	2016	20	23	19	21	22	21
	2017	24	25	22	29	30	25
Inactive covariates							
E-bike trip on reporting day[b] (%)	Work	1	12	8	11	4	5
	School	0	0	0	1	12	0
	Shopping	11	6	13	12	3	11
	Leisure	15	9	12	13	8	13

[a] *RO* retired older leisure users, *MF* middle-aged fulltime working people, *OF* older female leisure users, *YF* younger part-time working women with children, *ST* students

[b] Respondents in the Dutch national travel survey report their travel behaviour for a single day. The shown percentages reflect the share of people that used the e-bike for that specific purpose on the reporting day

Identifying the various e-bike user groups not only revealed groups who frequently use the e-bike, but also those who are not yet using e-bikes. Notably, for example, the various user groups rarely included 20 to 40 year olds; for example, in Group 2, comprised mainly of people with full-time jobs, only 10% of users are aged between 20 and 40 years old. Group 4 meanwhile has the most users aged 20 to 40: 29% of those in this group are aged between 20 and 40 years old with the majority of users having part-time jobs.

Trends in e-bike user groups

As indicated, the discussed class sizes in the previous section reflect the average class sizes over the years 2013 through 2017. As the year that a respondent participated in the Dutch national travel survey is known, the class sizes can be computed per year. Furthermore, population weight factors are included in the national travel survey. These weight factors are calculated based on a number of background characteristics such as age, gender, income and possession of means of transport (Statistics Netherlands 2018). With these weight factors, the absolute sizes of the different classes per year are calculated. This provides insight into how the five groups have grown over the years.

The shares and absolute sizes of the five groups over the years are shown in Table 8. The absolute sizes are rounded to the nearest thousand as it cannot be assumed that the weight factors in the national travel survey are accurate enough to calculate more detailed numbers. They are, however, believed to give a good indication of the absolute sizes.

Between 2013 and 2017, the total number of e-bike users grew from approximately 1.2 million to over 2 million people, an increase of 74%. In 2017, the Netherlands had 17.1 million inhabitants, resulting in just under 12% of Dutch people owning an e-bike. Looking at the increases in the individual groups, it becomes apparent that the two groups with the oldest users, the first and third group, show a slower growth rate of 50 and 39% respectively. As a result, the shares of these two groups (compared to all e-bike owners at one point in time) declined over the years. While the first group had a share of just over 56% in 2013, the share in 2017 was just under 49%. A growing share is visible for the second,

Table 8 Development of the e-bike user groups, share and absolute size

Share	Group 1	Group 2	Group 3	Group 4	Group 5	Total (×1000)
2013	56.1%	17.9%	15.4%	9.2%	1.3%	1170
2014	53.8%	19.8%	14.5%	10.5%	1.3%	1369
2015	49.5%	22.9%	15.4%	10.7%	1.5%	1630
2016	49.8%	24.5%	12.6%	11.4%	1.7%	1832
2017	48.6%	23.6%	12.3%	13.6%	1.9%	2033
Absolute size (×1000)	Group 1	Group 2	Group 3	Group 4	Group 5	
2013	657	209	180	108	16	1170
2014	737	272	199	144	18	1369
2015	807	374	250	175	24	1630
2016	912	449	230	209	32	1832
2017	988	480	250	276	39	2033
Growth 2013–2017	Group 1	Group 2	Group 3	Group 4	Group 5	Total
Growth (%)	50%	129%	39%	156%	150%	74%

fourth and fifth group. These three groups more than doubled in size in 5 years. This also explains the relatively large growth of the share of work related e-bike kilometres as discussed in the “Introduction”, as these groups use the e-bike primary for work- of education related trips instead of only for leisure of shopping.

Relatively speaking, the younger part-time working women with children (group 4) is growing the fastest. Next to this, the growth rate of the fifth class (consisting of young people) also stands out. From a substantive viewpoint, several reasons can be identified explaining why the e-bike is becoming popular among students and pupils. First, while many students and especially pupils live relatively close to their educational location, some live too far away to travel with a regular bicycle. In this case, the e-bike may offer an attractive (and in some cases cheaper) alternative to public transport. This may especially be the case in more rural areas of the Netherlands. And secondly, up to 2010 people in The Netherlands of 16 years and older were allowed to drive a scooter/moped after passing a theory exam. This was a relatively popular mode for pupils. In 2010, the age limit was raised to 17 and a practical exam was introduced, lowering the attractiveness of a scooter/moped. The e-bike may be seen as an alternative to a scooter/moped.

While in absolute terms the fifth segment is still quite small, the fact that a group of young people is now taking up this mode of transport means that the traditional image of the e-bike (as a mode of transport for elderly people, see Hendriksen et al. (2008)) is indeed shifting. As the image was previously found to be an inhibiting factor, this trend may therefore be expected to boost the adoption of the e-bike.Fig. 3 shows the growth of each user group compared to 2013. It is clear from the graph that the first and third group have been growing slower than the average growth of all groups since 2013. Although no data is available after 2017, it is not expected that these trends will suddenly change. Therefore it is expected that the three younger groups (group 2, 4 and 5) will keep growing at a higher rate. As these groups use the e-bike primarily for commuting or education, the shares of these trip purposes will keep growing. Furthermore, it is likely that substitution effects will become more evident due to these trends. If more people start using the e-bike for commuting, it is likely that the substitution effect that e-bike trips have on car trips can also be observed on the general level.

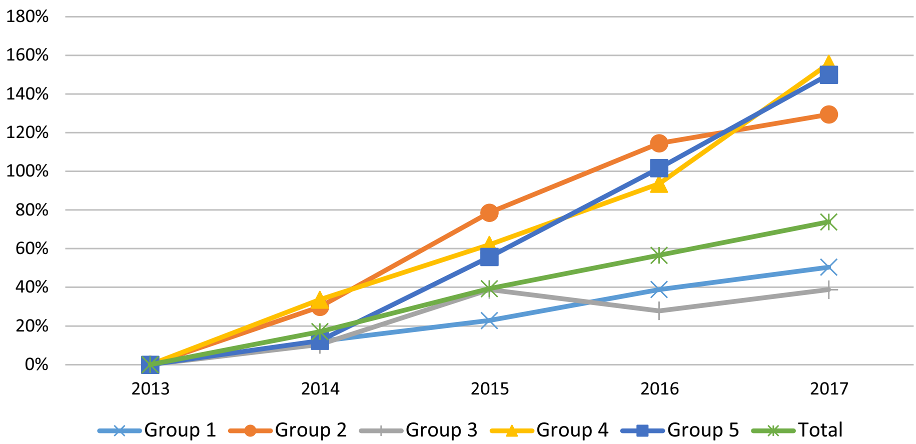

Fig. 3 Growth of e-bike user groups compared to 2013

Conclusions and future research

In this study, different user groups of the e-bike are revealed and substitution effects of the e-bike are examined based on longitudinal data to study substitution patterns and cross-sectional data to infer user groups. The main contributions of the present study are that substitution effects of the e-bike are identified based on longitudinal data and that trends in different e-bike user groups are analysed based on cross-sectional data to assess whether it is likely that substitution effects will change in the future. Our approach allows us to draw conclusions regarding substitution effects in terms of within-person changes in e-bike use and the use of other modes.

Conclusions

The present study is the first that uses a large-scale panel to address the question of substitution effects of using an e-bike. By making use of a Random Intercept Cross-Lagged Panel Model, within-person substitution effects are revealed. The outcomes show that in general, e-bike trips only substitute conventional bicycle trips. Specifically for commuting trips it was found that e-bike trips do substitute car trips, but this effect is not (yet) strong enough to be observed when modelling all trip purposes together. This contradicts earlier studies that often conclude that the e-bike also replaces the car and public transport to a certain level, and highlights the importance of using longitudinal data when doing such analyses.

Our finding that the e-bike is only substituting the conventional bicycle at a general level (i.e. combining all trip purposes), raises the question whether the e-bike has a positive effect on the environment, road congestion and health. Although there are no emissions while using the e-bike, there are charging-related emissions, making the e-bike less environmentally friendly compared to the conventional bicycle (Otten et al. 2015). With regards to health, several studies have shown that using an e-bike can be regarded as physical activity, but the level of intensity is lower compared to a conventional bicycle (Bourne et al. 2018).

Based on 5 years of data from the Dutch national travel survey we find that there are five different user groups within the e-bike population, each having a distinct usage pattern and socio-demographic composition. These groups range from the classical e-bike users in the Netherlands, the retired older people who use the e-bike primarily for leisure purposes to a (small) group of students who use the e-bike for education related trips. Although the first group is still the largest, its growing at a slower rate compared to the user groups that use the e-bike primarily for work or education purposes. Due to these trends in the different user groups of the e-bike, it is likely that substitution effects will change in the future. When enough people with a job own an e-bike, the substitution effect for commuting can probably also be observed on the general level.

Findings from the literature overview indicated that local context plays in a role in the substitution effects of the e-bike. Due to the important role of the bicycle in daily mobility in the Netherlands, it is likely that the results from this study are only valid for the Netherlands and countries where cycling is popular, such as Denmark or Germany.

Policy recommendations

From a policy point of view, we can draw important implications from the present study. Again, as local context is relevant, it is likely that these policy recommendations are only valid for the Netherlands and countries where the bicycle is popular, such as Denmark or Germany. The five different user groups show the profiles of people who are already adopting the e-bike. Apparently, people with these profiles are open to using an e-bike. Therefore, it might be relatively easy to promote the e-bike by specifically targeting these groups. For instance, the second largest e-bike user group consists of middle-aged full-time workers who primarily use the e-bike for commuting. To promote e-bike use among people with this profile who do not own an e-bike yet, a trial period in which people can experience their commute by e-bike might be effective in promoting the e-bike. Several companies and government agencies already started to offer this to their employees in the Netherlands.

On the other hand, promoting the e-bike among groups who are underrepresented in the e-bike population might be more difficult. For instance, 21–40 year olds as well as unemployed people are underrepresented in the e-bike population. To design effective policies to promote the e-bike among these groups more research is needed to determine why these people are not (yet) adopting the e-bike.

Furthermore, while on a general level only a substitution effect on the conventional bicycle is observed, the user groups that are growing at the highest rate are the groups that use the e-bike for commuting. Apparently, the working population is just starting to discover the e-bike as a mode of transport. As the e-bike substitutes the car (as well as other travel modes) for commuting trips, promoting e-bike use among employed people may result in a modal shift from car towards e-bike. This may result in positive effects on the environment, health and congestion.

Directions for future research

A limitation of this study is that it is unknown why people purchased an e-bike. This is important to know as it has an impact on the potential of the e-bike in terms of substitution effects. It could, for instance, be the case that the respondents that show a decrease in car use due to using the e-bike for commuting already had the desire to reduce their car use for commuting. If people only substitute the car by e-bike if they have this desire, promoting the e-bike among current non-users may have lower usage levels and substitution effects than expected by policy makers. In general, we hypothesize that those who bought an e-bike in ‘early’ years (when the e-bike was relatively expensive) use it more regularly than those who might choose to buy an e-bike in future years (possibly stimulated by monetary incentives from the government). The reason for this hypothesis, is that early adopters willing to spend a considerable sum of money on an e-bike, will most likely have done so based on the expectation that they will frequently and intensively use the e-bike for their personal travel. In contrast, those who currently do not own an e-bike but might be lured into buying one in future years as they get cheaper (possibly aided by tax-incentives), will be likely to use it less often than those early adopters—otherwise they would have bought one already when prices were higher. Assessing the motivations behind purchasing an e-bike would be an interesting avenue for future research, with clear and profound policy-relevance. This will also help in understanding why certain groups of people are not (yet) adopting the e-bike.

Another direction for future research arises from another limitation of this study. As the five identified user groups are different from each other in terms of sociodemographic and in terms of their purpose for using the e-bike, it might be that the substitution effects also differ between these groups. While the LCA made use of data from the Dutch national travel survey, the MPN includes the same indicators, making it possible to include MPN respondents in the LCA in order to identify to which user group each respondent belongs. However, as the MPN is relatively small compared to the national travel survey, the number of respondents per user group is too low to model substitution effects per user group. However, if e-bike ownership is developing at the same rate the coming years, the number of e-bike users within the MPN will also grow allowing for the estimation of the RI-CLPM per user group.

A third direction for future research is to study the relation between time-invariant factors and substitution effects. As the RI-CLPM assesses substitution effects at the within-person level, time-invariant factors are automatically controlled for. As a result, it is unclear whether these time-invariant factors play a role in the substitution effects. However, substitution effects might be influenced by these factors. For instance, Kroesen (2017) showed that e-bike ownership decreases with residential density. It may be that people in more rural areas are less open to the e-bike because travel distances are too high. This may also have an influence on substitution effects. It is therefore relevant to assess the effects of time-invariant factors on substitution effects.

Another direction is to also look at other effects than substitution. An earlier study by Kroesen (2017) concluded that e-bike ownership has a generative effect on the total distance travelled. As this study was based on cross-sectional data, it would be interesting to assess this effect based on panel data. If the e-bike indeed results in larger travelled distances, it might be that the effect that e-bike has on health is positive, even if it is also substituting the conventional bicycle at the same time.

A fifth direction for future research is to assess the distance that people find acceptable to travel by e-bike. In the present study, trips of all distances are included, but for long trips it may be assumed that people do not consider the e-bike as an option. By taking acceptable distances into account, substitution effects can be estimated for trips that could, in theory, be travelled by e-bike. It can, for instance, be expected that substitution effects for commuting are larger among people who live within 15 to 20 km from their work compared to people who live further away.

A final direction for future research is related to the segmentation of the e-bike population. In the latent class analyses, we made use of all e-bike owners in the Dutch national travel survey. A limitation of this is that people who use an e-bike but are not e-bike owners are not included in the segmentation. This could for instance be users of e-bike sharing systems. As indicated, these systems are not widely available yet in the Netherlands. However, if these sharing systems will play a more significant role in e-bike use in the future, it is relevant to study the user groups of these systems.

Acknowledgements A previous version of this paper was presented at the 8th Symposium of the European Association for Research in Transportation (hEART), Budapest, Hungary and at the 2nd Annual Meeting of the Cycling Research Board, Delft, The Netherlands in 2019.

Authors contributions MH research design, data analysis, results interpretation, lead paper writing, MK research design, results interpretation, paper writing, CC results interpretation, paper writing, SHL results interpretation, paper writing, SH results interpretation, paper writing.

Funding The corresponding author declares that the Authors did not receive any specific funding for this work.

Data availability Data from the Dutch national travel survey (OViN) and the Netherlands Mobility Panel (MPN) are available after requesting permission. Data from the Dutch national travel survey (OViN) are available through https://easy.dans.knaw.nl. Data from the Netherlands Mobility Panel (MPN) are, 2 years after data collection, available through https://www.mpndata.nl.

Code availability The RI-CLPM is estimated using the R package lavaan. The LCA is estimated using the statistical software package LatentGold. Model codes of both analyses are available from the corresponding author (MH) on request.

Declaration

Conflict of interest On behalf of all authors, the corresponding author states there is no conflict of interest.

References

Bourne, J.E., Sauchelli, S., Perry, R., Page, A., Leary, S., England, C., Cooper, A.R.: Health benefits of electrically-assisted cycling: a systematic review. Int. j. Behav. Nutr. Phys. Act. **15**(1), 116 (2018)

Brown, T.A.: Confirmatory Factor Analysis for Applied Research. Guilford Publications (2014)

Cherry, C., Cervero, R.: Use characteristics and mode choice behavior of electric bike users in China. Transp. Policy **14**(3), 247–257 (2007). https://doi.org/10.1016/j.tranpol.2007.02.005

Cherry, C.R., Yang, H., Jones, L.R., He, M.: Dynamics of electric bike ownership and use in Kunming, China. Transp. Policy **45**, 127–135 (2016)

CONEBI: European Bicycle Market 2017 Edition. Industry & Market Profile, Brussels (2017)

Enders, C.K., Bandalos, D.L.: The relative performance of full information maximum likelihood estimation for missing data in structural equation models. Struct. Equ. Model. **8**(3), 430–457 (2001)

Fietsersbond. Nederland fietsland. Retrieved October 6th, 2020 (2019). https://www.fietsersbond.nl/nieuws/hoe-hard-wij-fietsenen-nog-veel-meer-interessante-fietsweetjes/

Golob, T.F., Meurs, H.: A structural model of temporal change in multi-modal travel demand. Transp. Res. Part A Gen. **21**(6), 391–400 (1987)

Hamaker, E.L., Kuiper, R.M., Grasman, R.P.: A critique of the cross-lagged panel model. Psychol. Methods **20**(1), 102 (2015)

Hendriksen, I., Engbers, L., Schrijver, J., van Gijlswijk, R., Weltevreden, J., Wilting, J.: Elektrisch Fietsen. Marktonderzoek en verkenning toekomstmogelijkheden. TNO, Leiden (2008)

Hiselius, L.W., Svensson, Å.: E-bike use in Sweden–CO_2 effects due to modal change and municipal promotion strategies. J. Clean. Prod. **141**, 818–824 (2017)

Hoogendoorn-Lanser, S., Schaap, N.T.W., OldeKalter, M.-J.: The Netherlands Mobility Panel: an innovative design approach for web-based longitudinal travel data collection. Transp. Res. Procedia **11**, 311–329 (2015). https://doi.org/10.1016/j.trpro.2015.12.027

Johnson, M., Rose, G.: Electric bikes–cycling in the New World City: an investigation of Australian electric bicycle owners andthe decision making process for purchase. Paper presented at the Proceedings of the 2013 Australasian Transport Research Forum(2013)

Jones, T., Harms, L., Heinen, E.: Motives, perceptions and experiences of electric bicycle owners and implications for health, wellbeing and mobility. J. Transp. Geogr. **53**, 41–49 (2016). https://doi.org/10.1016/j.jtrangeo.2016.04.006

Kennisinstituut voor Mobiliteitsbeleid. Mobiliteitsbeeld 2019. Kennisinstituut voor Mobiliteitsbeleid, The Hague (2019)

Kroesen, M.: To what extent do e-bikes substitute travel by other modes? Evidence from the Netherlands. Transp. Res. Part D Transp. Environ. **53**, 377–387 (2017). https://doi.org/10.1016/j.trd.2017.04.036
MacArthur, J., Dill, J., Person, M.: Electric bikes in North America: results of an online survey. Transp. Res. Rec. j. Transp. Res. Board **2468**, 123–130 (2014)
MacArthur, J., Cherry, C., Harpool, M., Scheppke, D.: A North American Survey of Electric Bicycle Owners. NITC-RR-1041. Transportation Research and Education Center (TREC), Portland, OR (2018). https://doi.org/10.15760/trec.197
Magidson, J., Vermunt, J.: Latent Class Models. The Sage Handbook of Quantitative Methodology for the Social Sciences, pp.175–198 (2004)
McCutcheon, A.L.: Latent Class Analysis. Sage Publications, Newbury Park (1987)
Montgomery, B.N.: Cycling trends and fate in the face of bus rapid transit: case study of Jinan, Shandong Province, China. Transp. Res. Rec. **2193**(1), 28–36 (2010)
Otten, M., Hoen, M.T., Boer, L.D.: STREAM personenvervoer 2014, versie 1.1. Studie naar TRansportEmissies van AlleModaliteiten Emissiekentallen. Emissiekentallen 2011. CE Delft, Delft (2015)
Rosseel, Y.: lavaan: an R package for structural equation modeling and more. J. Stat. Softw. **48**(2), 1–36 (2012)
Shao, Z., Gordon, E., Xing, Y., Wang, Y., Handy, S., Sperling, D.: Can electric 2-wheelers play a substantial role in reducing CO_2 emissions? Institute of Transportation Studies (2012)
Statistics Netherlands. (2013–2017). Netherlands Travel Survey (OViN)
Statistics Netherlands: Onderzoek Verplaatsingen in Nederland 2017: Onderzoeksbeschrijving. Centraal Bureau voor de Statistiek, The Hague (2018)
Stichting BOVAG-RAI Mobiliteit: Fietsen in de statistiek 2011–2018 (2019)
Sun, Q., Feng, T., Kemperman, A., Spahn, A.: Modal shift implications of e-bike use in the Netherlands: moving towards sustainability? Transp. Res. Part D Transp. Environ. **78**, 102202 (2020)
Vermunt, J., Magidson, J.: Latent class cluster analysis. In: Hagenaars, J.A., McCutcheon, A.L. (eds.) Applied Latent Class Analysis, pp. 89–106. Cambridge University Press, Cambridge (2002)
Vermunt, J., Magidson, J.: Latent GOLD 4.0 User's Guide. Statistical Innovations Inc, Belmont (2005)
Weinert, J., Ma, C., Cherry, C.: The transition to electric bikes in China: history and key reasons for rapid growth. Transportation **34**(3), 301–318 (2007a). https://doi.org/10.1007/s11116-007-9118-8
Weinert, J., Ma, C., Yang, X., Cherry, C.R.: Electric two-wheelers in China: effect on travel behavior, mode shift, and user safety perceptions in a medium-sized city. Transp. Res. Rec. **2038**(1), 62–68 (2007b)
Wolf, A., Seebauer, S.: Technology adoption of electric bicycles: A survey among early adopters. Transp. Res. Part A Policy Pract. **69**, 196–211 (2014). https://doi.org/10.1016/j.tra.2014.08.007

Mathijs de Haas is a researcher at the Netherlands Institute for Transport Policy Analysis (KiM) and a PhD student at the Delft University of Technology. His main research topic is person mobility, with a focus on active modes (walking and cycling). Using longitudinal data, he studies causal processes underlying travel behavior change.

Maarten Kroesen is an Associate Professor in Travel Behaviour Research at the Faculty of Technology Policy and Management at Delft University of Technology, the Netherlands. His research focuses on active modes, particularly in relation to health and uncovering complex causal structures using panel data.

Caspar Chorus is professor of Choice behavior modelling and head of the Engineering Systems and Services department at Delft University of Technology. He received his PhD (highest distinction) from TU Delft, for his dissertation "Traveler response to information". His current research focuses on developing and testing models of moral and boundedly rational decision making for humans and artificial intelligence.

Sascha Hoogendoorn-Lanser is director of the Mobility Innovation Centre Delft. She is responsible for setting up, facilitating, implementing and disseminating (the results of) pilot projects of new concepts for personal mobility and distribution.

Serge Hoogendoorn (Distinguished Professor of Smart Urban Mobility and chair of the Transport & Planning department at Delft University of Technology), analyzes the individual and collective behavior of cyclists, pedestrians and drivers of motorized vehicles, to avoid crowding and congestion. With his models, he seeks to prevent traffic jams, respond appropriately to emergencies, and counteract high, corona-hazardous concentrations of people.

Authors and Affiliations

Mathijs de Haas[1] · **Maarten Kroesen**[2] · **Caspar Chorus**[2] · **Sascha Hoogendoorn-Lanser**[3] · **Serge Hoogendoorn**[4]

[1] KiM Netherlands Institute for Transport Policy Analysis, Bezuidenhoutseweg 20, 2594 AV The Hague, The Netherlands

[2] Faculty of Technology, Policy and Management, Delft University of Technology, Jaffalaan 5, 2628 BX Delft, The Netherlands

[3] Valorisation Centre, Delft University of Technology, Van der Burghweg 1, 2628 CS Delft, The Netherlands

[4] Faculty of Civil Engineering and Geosciences, Delft University of Technology, Stevinweg 1, 2628 CN Delft, The Netherlands