Assessing the Long-term Impact of E-bikes on Sustainable Mobility: A National-Level Study in the Netherlands

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SHORT SUMMARY

Over the past decade, e-bikes have become increasingly popular, sparking interest in their potential replacement for car use and benefit for the environment. However, studies on e-bike substitution effects have limitations, including a lack of assessments of the effects on mobility on the national level, a narrow focus on commuting travelling, and insufficient consideration of future expected e-bike use. This study proposes a new approach that combines an intention-based method with time-series forecasting to estimate e-bike use and investigate its potential for sustainable mobility in the Netherlands. The results show that e-bike ownership strongly reduces the conventional bicycle use and, to a lesser extent, car and public transport use, especially for commuting travelling. This study provides insight into how e-bikes substitute for car use and other modes of transportation, and how the expected growth in e-bike use in coming years may impact national mobility in the Netherlands.

Keywords: Matching method, Unified-Richards growth curve, Transport policy, Cycling behaviour, Substitution, Dutch national mobility survey

1. INTRODUCTION

Pedal-assisted-bikes, also known as e-bikes or electric bikes, are bicycles equipped with a battery-powered motor that assists with pedalling, providing support up to a maximum speed or power. E-bikes have increased in popularity over the past decade. In Europe, e-bike growth per year has an average of 30% between 2010 and 2016. Germany and The Netherlands accounted for over 50% of e-bike sales in the EU in 2016 (CONEBI 2017). In the Netherlands, since 2018, more new e-bikes have been sold each year than conventional bikes (BOVAG, 2023). Moreover, more younger aged people are adopting the e-bike which was originally popular among people over the age of 65 in the Netherlands. 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 car trips and bring health benefits. It is thus worth investigating the potential contribution of e-bikes in the shift towards a more sustainable transport system.

Previous studies have shown that the sustainability effects of e-bikes are complex. It mainly depends on whether the e-bike replaces motorized modes (e.g. car trips) (Wolf and Seebauer, 2014). In reality, whether e-bike use will result in a reduction of car use depends on local context. For instance, the substitution of public transport by e-bikes happens in cities with a high-quality transit system (Fishman and Cherry, 2016). The substitution of car trips can be observed in a car-dominated countries (Wolf and Seebauer, 2014), whereas in European countries with a bicycle orientation, the e-bike seems to substitute the conventional bicycle in addition to the car (Cherry et al., 2016; de Haas et al., 2021; Kroesen, 2017).

A limitation of previous studies is that they are not representative for mobility on the national mobility level nor focused on the future expected e-bike adoption and use. These studies typically focus on individual-level effects with selective survey samples, which may be representative of the national population, but not necessarily of national mobility. While evidence on substitution effects can be collected from such studies, assessing the effect of e-bikes on mobility on the national level is difficult. Moreover, previous studies tend to focus specifically on commuting and do not consider the use of the e-bike for other trip motives. Due to these limitations, the current knowledge on e-bike substitution effects provides an incomplete picture. This limits policymakers in making well-informed decisions on how to use e-bikes to promote sustainable travel behaviour. This study addresses these shortcomings by assessing the effects of e-bike substitution over the long term at a national mobility level in the Netherlands, a leading country in e-bike adoption (Fishman and Cherry, 2016; CONEBI 2017).

We aim to provide a new approach to tackle the question of e-bike adoption and usage at the national level in the long run, and we provide a robust validation of our findings. For this purpose, we employ a combination of an intention-based method and a time-series forecasting method to estimate e-bike use and travel behaviour in the future, providing insights into the substitution of other transport modes in the Netherlands. These insights can be used by policymakers to decide if, and how, the e-bike can be used as a means of promoting more sustainable travel behaviour.

2. METHODOLOGY

To investigate how e-bikes can replace other modes of transportation, we used a combination of an intention-based method and time-series models to estimate e-bike use in the coming years. The intention-based method estimates future e-bike ownership, e-bike use and travel behaviour based on people’s intention to buy an e-bike and their intended use of the e-bike by using the Netherlands Mobility Panel (MPN). Further, we validated this estimation by a time series forecasting method based on data from the Dutch national travel survey from 2013 to 2021 (Statistics Netherlands, 2013–2021).

Intention-based method

To predict future e-bike ownership and usage, we used a two-step approach. First, we collected people’s intention to purchase an e-bike within the next five years and their intended use of the e-bike using the annually conducted Netherlands Mobility Panel (MPN) from the year 2021 (KiM, 2021). Second, we estimated the future national-level e-bike use and other modes of transport by assuming that those with a buying intention will purchase e-bikes and their usage will mirror that of current e-bike owners with similar demographic profiles. This assumption is based on the finding from the first step that future e-bike owners intend to use the e-bike in a similar manner to current owners.

For the first step, the MPN, an annual household panel that represents the Dutch population, was used to gather data on future e-bike buying intentions. A total of 1046 e-bike owners and 1461 non-owners participated in the questionnaire. For the second step, the Dutch national travel survey (ODiN) was used to predict future e-bike usage and travel behaviour. The annually conducted ODiN involves approximately 40,000 individuals (0.2% of the Dutch population) and is representative of the daily mobility of the Dutch population.

ODiN provides more reliable information on yearly statistics of total Dutch mobility than MPN. But MPN is more practical to collect e-bike buying intention. The two datasets were connected through a matching process as shown in Figure 1 in order to link the future adoption intention gathered from MPN to ODiN. Since ODiN includes more respondents than MPN, the matching process involved linking each MPN respondent with buying intention to multiple ODiN respondents with the same sociodemographic profile and do not yet own an e-bike. This allowed us to identify individuals in ODiN who do not own an e-bike, but do intend to purchase one in the near future.

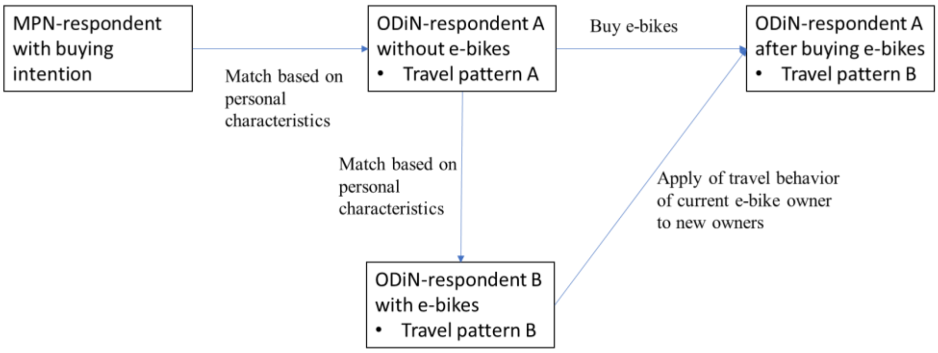

Figure 1 Schematic representation Calculation potential e-bike

To further estimate the e-bike use of future owners in ODiN and their travel behaviour on the national level, we assume that the future e-bike owners will use their e-bikes in a similar manner as current owners with similar demographic profiles. This assumption is backed by the MPN survey, that showed that future e-bike owners expect to use the e-bike in a similar manner as current owners. To do so, we replaced the travel diaries of the future e-bike owners with the travel diaries of their matched e-bike owners in ODiN. The new ODiN data is still representative of the mobility of the Dutch population in the five years following the reference year 2019. Respondents were matched based on personal characteristics available in both MPN and ODiN, such as gender, age, urbanity, education level, car ownership, and commute distance, using the Mahalanobis distance and the R-package MatchIt (Stuart et al., 2010).

The estimate of the e-bike use presented above does not take into account other relevant factors that may affect usage, such as demographic and economic developments. Therefore, we do not have a complete picture of the expected development of the e-bike use. Furthermore, this estimate is based on a number of key assumptions as described above However, our second method can partially address this issue by validating the results using a time series model.

Time series forecasting

The goal of the time series forecasting is to model the e-bike share and extrapolate the share to 2024, so as to evaluate the e-bike usage results from the above mentioned intention-based method. This method only extrapolates the future e-bike share and provides no information about e-bike substitution and future usage of other transport modes.

The e-bike share was estimated with a multilevel time series models (MTSM). The combination of fixed and random effects of the MTSM allows the sharing of information across all group aggregates (5 travel purposes, 9 age groups and 2 genders). This results in more precise estimates as compared to modelling each group separately. Assuming that the e-bike share follows an S-shaped growth process in general, we applied the Unified-Richards growth curve formulation (1) of (Vrána et al., 2018) in the MTSM because it covers a wide range of S-shaped growth curves.

$$w = A(1 + (d-1) * \exp(\frac{-k_U(t-T_i)}{d^{d/(1-d)}}))^{1/(d-1)} + b_1 * cvd_1 + b_2 * cvd_2 \qquad (1)$$

The Unified Richards growth curve parameters are:

1. saturation level A (the upper asymptote of the share curve).
2. (relative) growth rate k_U at the inflection point of the growth curve.
3. time-location T_i of the inflection point. (t represents time)
4. form parameter d that locates the vertical location of the inflection point.

Additionally, the effect of the COVID-19 pandemic on e-bike share in 2020 and 2021 was modelled by the parameters b_1 and b_2 respectively, with corresponding dummy variables cvd_1 and cvd_2.

Each parameter was modelled as follows. The fixed effects of the parameters A, k_U and T_i were modelled as a monotonic function of age (Bürkner & Charpentier, 2020), with gender added for parameter A. Additional fixed effects are the interaction of gender and age for parameter d and the interaction of age and purpose for parameters b_1 and b_2. Random effects varying over all combinations of purpose, age and gender were included for parameters A, k_U, b_1 and b_2 and varying over purpose and gender for parameter d. The random effects of the parameters A and k_U were modelled as correlated.

The multilevel model was fitted to ODiN data form 2013 to 2021, using the R-package brms (Bürkner 2017). Brms is an interface to the Bayesian Markov Chain Monte Carlo programming language Stan (Stan Development Team, 2022). Model checking and model comparison were done using goodness of fit values of the waic information criterion and approximate leave-one-out cross validation using the R-package loo (Vehtari et al., 2017).

3. RESULTS AND DISCUSSION

Over the next 5 years, the MPN survey results suggest that 22% of non-owners intend to adopt an e-bike (see Table 2). However, it is likely that not all of these individuals will actually end up purchasing an e-bike. To provide a realistic estimate, we assume that all individuals with an intention to buy within the next 6 months will make a purchase, while 90% of those intending to buy within the next 2 years, and 85% of those intending to buy within the next 5 years will eventually buy an e-bike by 2024.

Table 2 Intention of e-bike adoption among non-owners

e-bike adoption	Share of the non-owners	Share that actually purchases an e-bike
yes, within 6 months	2%	100%
yes, between 6 months – 2 years	8%	90%
yes, between 2-5 years	12%	85%
yes, but after 5 years	17%	-
No	61%	-

If we take into consideration the increase in e-bike ownership and the travel habits of the new owners, the distance covered by e-bike is expected to rise to 69% between 2019 and 2024, from 0.65 km per person per day to 1.1 km per person per day. The distance covered by regular bicycles will then drop by 10%. The total distance covered by e-bike will rise more than the distance covered by regular bicycle will decrease, causing the total distance covered by bicycle to increase by about 8%. This will cause the e-bike's share of the total distance covered by bicycle to increase from 23% to 35%. This e-bike share estimation is in line with our time series forecasting result, as shown in Figure 2.

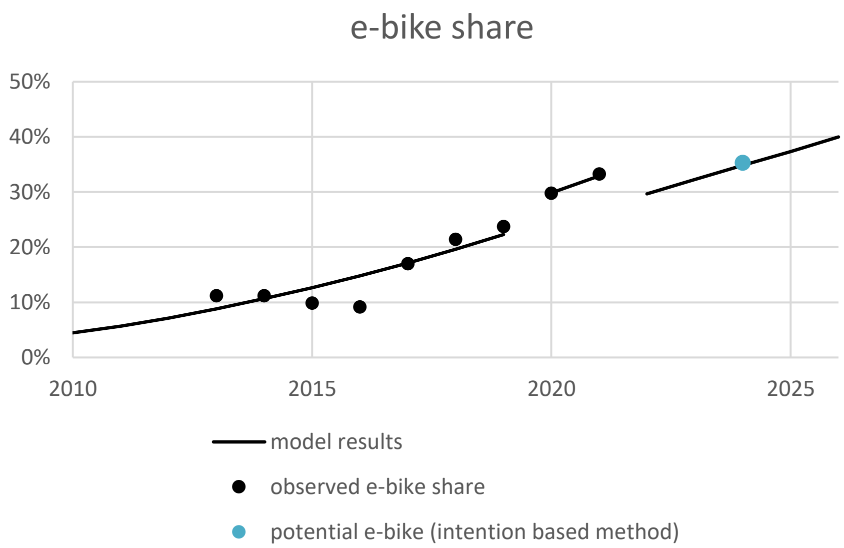

Figure 2 The forecasting of the e-bike's share of the total distance covered by bicycle based on time series forecasting

E-bikes also substitute other means of transport than the regular bicycle. Figure 3 shows the changes in the share of trips for a number of transport means classified by distance. It shows the regular bicycle being substituted by the e-bike for distances under 7 km, while the use of the car (as driver) also slightly declines for longer distances above 7 km. Additionally, short-distance BTM trips and long-distance train trips have both decreased, but due to the small sample sizes of these types of public transportation trips in ODiN, it is difficult to draw strong conclusions from these findings. Moreover, car passenger trips above 25 km show a slight increase, but more other evidence, such as longitudinal analysis, is needed to make definitive conclusions on the effects of the e-bike car passenger use and public transport use.

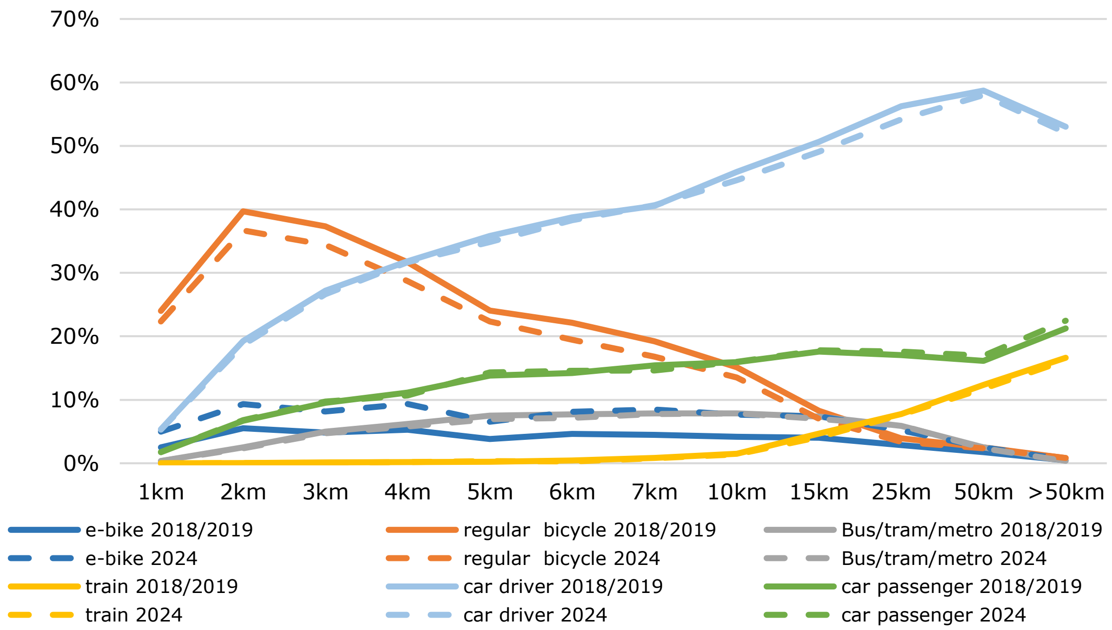

Figure 3 Effect of expected development of e-bike ownership on the modal split classified per distance by intention-based method

The development of e-bike ownership does not lead to an equally large increase in e-bike use for all purposes (see Figure 4). A relatively high number of working people intend to buy an e-bike. Therefore, we expect that the e-bike will have the largest impact on commuter traffic. E-bike use could rise by 122% for this purpose. The e-bike's share of the distance that commuters cover by bicycle would then rise from 23% to 44% and the total distance cycled for this purpose would rise by about 17%. The e-bike currently accounts for a quarter (26%) of all bicycle trips made for leisure or for shopping, this share will increase to 40% and 36% respectively. For both purposes, the total distance covered by bicycle would increase by about 5%. The use of the e-bike for going to school would increase by 110%, which would increase the e-bike's share in the total distance covered by bicycle from 7% to 14%. The total distance covered by e-bike would also increase by about 5% for this purpose.

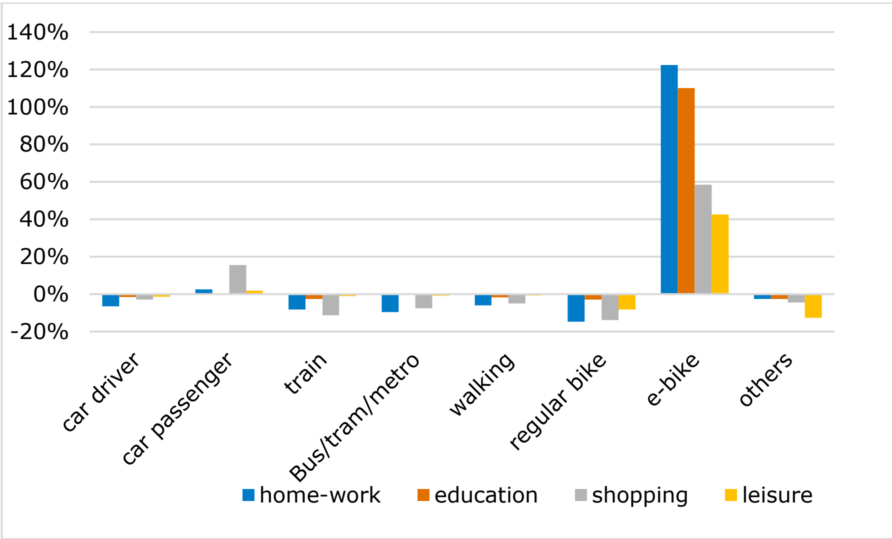

Figure 4 Changes in distances covered per purpose per means of transport by intention-based method

4. CONCLUSIONS

We estimate the role of e-bikes in the five-year period from 2019 to 2024, taking into account the growth in e-bike ownership and travel behaviour of new e-bike owners. To validate our findings, we also used time series forecasting to cross-check the e-bike share estimation.

We find the distance covered by e-bikes is expected to increase significantly between 2019 and 2024, while the distance covered by regular bicycles is expected to decrease, with e-bikes primarily substituting regular bicycles on shorter distances. We expect that the use of e-bikes for commuting will increase significantly and that there may be a reduction in car use for longer distances. Furthermore, there is a possibility that e-bike use will lead to a decrease in public transport use, including bus/trams/metros and train, in the future.

The expected substitution of car use by e-bikes represents a positive contribution to sustainable mobility. This indicates that, to a certain extent, promoting e-bike use results in a shift towards more sustainable travel behaviour. At the same time, promoting e-bike use may also result in a reduction of the normal bicycle and public transport. If policymakers want to promote e-bike use, our previous study(de Haas & Huang, 2022) identified a number of key action points that policymakers could use to develop policies aimed at encouraging use of the e-bike. These include improving facilities and infrastructure such as guarded bicycle parking facilities and broader cycle paths with safer crossing points, increasing the cost of other modes of transport like cars and addressing barriers to commuting such as improving facilities at the work place (e.g., showers, changing areas, and providing secure bicycle parking).

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