Journal of Cycling and Micromobility Research 2 (2024) 100027

Contents lists available at ScienceDirect

Journal of Cycling and Micromobility Research

journal homepage: www.sciencedirect.com/journal/journal-of-cycling-and-micromobility-research

Assessing the E-bike trends and impact on sustainable mobility: A national-level study in the Netherlands

Bingyuan (Amelia) Huang *, Hans Wüst, Mathijs de Haas

KiM Netherlands Institute for Transport Policy Analysis, Bezuidenhoutseweg 20, The Hague 2594 AV, the Netherlands

ARTICLE INFO

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

ABSTRACT

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, many studies on e-bike development and their substitution effects exhibit limitations. These include a lack of modeling on e-bike trend development, inadequate assessments of their impact on national-level mobility, a predominant focus on commuting, and a lack of foresight into future e-bike substitution effects. Our research introduces an innovative approach to model e-bike development, employing a multilevel Richards growth curve model fitted within a hierarchical Bayesian framework using the Hamiltonian Monte Carlo (HMC) method. Further, we incorporate an intention-based method to delve into the potential of e-bikes in stimulating sustainable mobility in the Netherlands. Our findings highlight an ongoing increase in e-bike distance share, with marked gender and generational differences in growth patterns. Notably, women have higher e-bike usage than men, and this gap is narrowing for older age groups while widening among younger demographics, suggesting that younger people may adopt e-bike usage differently than older generation. E-bike ownership strongly reduces the conventional bicycle use and, to a lesser extent, car and public transport use, especially for commuting. This study provides insight into whether and to what extent 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.

1. Introduction

Pedal-assisted-bikes, also known as e-bikes or electric bicycles, are bicycles equipped with a battery-powered motor that assists with pedaling, providing support up to a maximum speed or power. In recent years, e-bikes have rapidly grown in popularity across Europe, offering an alternative to less environmentally-friendly modes, such as the car, carrying potential environmental benefits.

The Netherlands, known for its vibrant bicycle culture, boasts a high e-bike adoption rate in the Europe relative to its population (de Haas and Hamersma, 2020; CONEBI, 2021; Stichting BOVAG-RAI Mobiliteit, 2022). As of 2021, two out of every ten individuals in the Netherlands own an e-bike, with 3 % of the Dutch population purchasing one annually. Historically, e-bike usage in the Netherlands was primarily leisure-oriented, with the elderly as the pioneering adopters. However, recent trends indicate a demographic shift in adoption. Younger users are increasingly choosing e-bikes, employing them more for work-related commutes rather than leisure (de Haas and Hamersma, 2020; de Haas et al., 2021; de Haas and Huang, 2022). This shift suggests e-bikes could increasingly replace car trips, thereby boosting their contribution to sustainability. However, a noticeable gap persists: comprehensive studies that focus on the adoption and influence of e-bikes on transportation systems remain sparse. In particular, there's a lack of large-scale, representative mobility surveys on e-bikes outside the European context. Even within Europe, dedicated research that models e-bikes within transportation systems for forecasting and policy evaluation is largely missing (Arning et al., 2023). Recognizing the pioneering role of the Netherlands in promoting e-bikes, our study seeks to address this research gap. We aim to provide insights into e-bike development trends across different purposes and user groups. Additionally, examining the substitution effect in regions with high e-bike adoption can provide insights into trends in countries just beginning to embrace e-bikes.

This paper aims to achieve two primary objectives. First, we intend to estimate and forecast the growth in distance covered by e-bikes across diverse segments, including various age groups, gender, and travel purposes, based on a comprehensive analysis of data from a large-scale national travel diary. Second, we conduct a comprehensive analysis

* Corresponding author.
E-mail address: Bingyuan.huang@minienw.nl (B.(A. Huang).

https://doi.org/10.1016/j.jcmr.2024.100027
Received 5 December 2023; Received in revised form 25 March 2024; Accepted 16 April 2024
Available online 17 April 2024

using 2019 national survey data to predict the potential of e-bikes to replace or reduce the use of cars, conventional bicycles and other transportation modes at a national level by 2024. As we delve into our findings, we will also highlight potential future research topics, particularly focusing on policy implications related to e-bike adoption and usage. In doing so, it is possible to throw light on whether individuals with different travel purposes and from differently age groups and generations develop different e-bike trends over time and achieve different e-bike substitution effects. These insights are tailored to assist policymakers in evaluating whether, and how promoting e-bike use can be an instrument for attain a more sustainable travel behavior.

2. Literature

2.1. E-bike models and substitution effect in previous research

In recent years, the study of e-bike use and demand has emerged as a vital research area, garnering significant academic interest because e-bikes promise a more sustainable transportation alternative and can positively impact individual well-being (fka Andersson et al., 2021; Jones et al., 2016; Kroesen, 2017; Rérat, 2021; Sun et al., 2020). Yet, dedicated research that models e-bikes within transportation systems is largely absent (Arning et al., 2023), with most existing studies primarily relying on surveys to understand e-bike adoption (Plazier, 2018; Simsekoglu and Klöckner, 2019). In many countries renowned for their robust cycling research, e-bikes and traditional bicycles are often grouped together and analyzed as a single mode. This is evidenced by existing micro-econometric/disaggregate models for cycling demand (Rayaprolu et al., 2020; Hallberg et al., 2021). The challenges in distinguishing e-bikes in these disaggregate models (mode choice or route choice modelling) arise from two main issues. First, there is lack of data about e-bike which is heavily relied on in disaggregate model. Second, e-bike adoption is influenced by numerous factors including technological innovations, shifting societal norms, and varying policy interventions, which complicates the task of estimating disaggregate level models (Arning et al., 2023). Despite these challenges, understanding the choices of current e-bike users and projecting future adoption remains crucial. The emergent nature of e-bikes and the variability in adoption stages add complexity to modeling approach. Although disaggregate models offer insights into early adopter behaviors, they might not accurately reflect the broader population as the e-bike market evolves. Aggregate models, which are more data-efficient and can discern the overall patterns and trends in e-bike use, provide a viable alternative for modeling e-bikes, especially during the early stages of their adoption.

E-bikes are gradually transitioning from being niche products to mainstream transportation tools in the Netherlands (KiM, 2023). Their adoption trajectory appears to trace an S-curve growth pattern, which is observed among elderly early adopters. This is supported by literature which shows that numerous technological innovations exhibit S-curve growth, which strengthens its potential relevance to e-bikes (Geroski, 2000; Rogers et al., 2014). Moreover, in the field of car ownership growth, studies have been found to use aggregate models with the sigmoid-shaped functions, e.g., the logistic, the Richards curve (Jong et al., 2004; Lu et al., 2017; Gan et al., 2020). These growth curve models offer distinct advantages in representing the stages of technology adoption — from initial uptake through rapid growth phases to eventual market saturation. Applying these models to e-bike adoption at an aggregated level can adeptly capture the initial excitement, the rapid adoption phase, and the eventual market saturation. This can shed light on potential maximum adoption rates and pinpointing inflection points – insights that are invaluable for both policymakers and industry stakeholders.

Prior research highlights the multifaceted sustainability implications of e-bikes. Their impact largely hinges on whether they substitute for motorized modes, notably cars (Wolf and Seebauer, 2014). This substitution effect, in practice, is influenced by the existing transportation dynamics of a region. In cities with advanced transit systems, e-bikes often replace public transport (Fishman and Cherry, 2016). In car-centric regions, there is a distinct shift from automobiles to e-bikes (Wolf and Seebauer, 2014). Meanwhile, in Europe, known for its bicycling culture, e-bikes frequently displace not just cars but also conventional bicycles (Cherry et al., 2016; Kroesen, 2017; de Haas et al., 2021). Given the high prevalence of both car and bicycle travel in the Netherlands, where approximately 29 % of trips are made by car and 26 % by bicycle (KiM, 2023), it is anticipated that e-bikes may increasingly substitute for these traditional modes.

In the Netherlands trends show that the e-bike substitution effect also varies with user demographics and generations. The elderly, for example, gravitate towards e-bikes when conventional cycling becomes challenging, whereas younger users show a noticeable shift from cars to e-bikes. As e-bikes gain traction among different demographics, these patterns are likely to evolve (de Haas et al., 2021). These emerging patterns indicate a generational pivot in transportation preferences, which is worth of future analysis concerning e-bike effects among different demographics and generations.

2.2. Contribution to literature and paper structure

The paper contributes to the literature by addressing the research gap in modelling e-bike with growth curve models and by analyzing e-bike substitution effects among different demographics and generations. We project the growth of e-bike use with S-curve models from other technological domains, allowing for a distinction between e-bike and conventional cycling patterns. Moreover, we provide insights into e-bike development trends across various travel purposes and different generations and demographic groups. Additionally, the paper investigates the substitution effect of e-bikes in the Netherlands, a region where e-bikes are prominently promoted. The paper offers a comprehensive view of this emerging mode of transport and sheds light on potential shifts in transportation system.

For clarity and coherence, the paper is structured to handle the two main studies: trend projection and substitution effect. These are treated as separate yet interrelated studies, each supported by its unique methodology, dataset, and analytical framework. We begin with an analysis of e-bike share trends and e-bike distance development among user groups (Study 1), presenting our methods, data, and results. This is followed by the analysis of substitution effects (Study 2). Even though both methods address future e-bike share, their focal points differ. Study 1 focuses on national e-bike trends projection, while Study 2 examines anticipated e-bike use based on individuals' intentions to use e-bikes. Notably, the findings of Study 1 could validate those of Study 2, leading to a comparative review of the two methods at the end.

3. Study 1: E-bike development

To understand the growth of e-bike use, we broke it down into two components, the development of e-bike share and the overall growth in e-bike distance. Firstly, we modelled the e-bike share development, defined as the ratio of the total e-bike traveled distance to the total bicycle traveled distance. A rising e-bike share would suggest that e-bikes are increasingly favored over conventional bicycles, even if the traveled distances for both types of bicycles are on an upward trajectory. One primary advantage of modeling e-bike share over direct e-bike distance is its ability to minimize year-to-year variances. This method is effective in smoothing out data irregularities that might result from periodic fluctuations in the distances cycled by e-bikes, since the ratio tends to be more stable over time compared to absolute distances. Secondly, we seek to gauge the overall e-bike distance growth. Once we've determined the e-bike share, we can ascertain the overall e-bike distance growth. This is deduced by multiplying the previously determined e-bike share with the overarching trend in total bicycle distance. Notably, data on the total bicycle distance trend is readily available, as modeled by institutions like CBS and KiM (Boonstra et al., 2021; KiM, 2023).

3.1. Method

We've employed the Unified Richards growth curve as presented in formula (1) (Vrána et al., 2019), to model the e-bike share (w). The e-bike market's evolution, marked by intricate adoption stages, necessitates a growth curve that can seamlessly capture these complex patterns of adoption stages. The Unified Richards growth curve emerges as an apt choice since it enhances the flexibility of the symmetric standard logistic growth curve with its additional form and time location parameters. The Richards curve allows for differences in the duration of the initial growth phase and the final saturation phase if necessary (Tjørve and Tjørve, 2010). This feature is particularly useful for capturing the asymmetry often seen in S-shaped growth trajectories, where the rise and fall of growth rates may not be mirror images of each other. This adaptability is especially relevant for the dynamic e-bike market, which may exhibit varying adoption patterns across different groups, not strictly in line with the logistic model. In various biological and ecological contexts, the Richards curve has proven its mettle in capturing complex growth trajectories, further cementing its applicability to analogous market growth scenarios (Tjørve and Tjørve, 2010; Vrána et al., 2019).

Further, a multilevel Bayesian hierarchical model was employed to estimate these growth curves. This methodology offers a distinct advantage, especially when examining segments with a relatively low e-bike adoption rates. Those segments often have limited data on e-bike travelled distance, which can be unreliable and with a high degree of variability. By "borrowing strength" from various segments as well as over time, we're able to draw insights from segments with a higher e-bike adoption rate, which in turn facilitates more reliable estimates for low e-bike adoption rate groups. Here the 'borrowing of strength' is brought about by using multilevel time series models with random effects for several levels of segments (Boonstra et al., 2021). In the field of official statistics, this concept known as small area estimation involves employing statistical models to enhance the precision of direct estimates in specific areas of interest. Rao and Molina (2015) offer a comprehensive review of this approach. The e-bike share growth curve model was fitted in a hierarchical Bayesian framework with a Hamiltonian Monte Carlo (HMC) method. The model estimates were computed at the most detailed domain level (5 travel purposes, 9 age groups and 2 genders). The combination of fixed and random effects of the multilevel model allows the sharing of information across all groups. This results in far more precise estimates as compared to modelling each group separately.

$$w = A(1 + (d-1) * \exp(\frac{-k_U(t-T_i)}{d^{d/(1-d)}}))^{1/(d-1)} \quad (1)$$

The Unified Richards growth curve parameters are:

1. saturation level A (the upper asymptote of the growth 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.

Each parameter was modelled as follows. The fixed effects of the parameters A, k_U and T_i were modelled with an intercept and a monotonic function of age (Bürkner and Charpentier, 2020). This ordinal approach stabilizes the estimates as the development of these parameters across age groups is predominantly monotonic. For parameter A and k_U, small deviations from this monotonic development (e.g., age group 30–39) were captured by a random effect component that varies across all combinations of purpose, age, and gender. Further, the random effects of A and k_U were modeled as correlated. The parameter d only had an intercept as a fixed effect and a random intercept structure varying over purpose and gender.

The Unified Richards growth curve's flexibility allows for the integration of external impacts into our model, ensuring accurate representation of real-world events. For example, we've modeled the impact of mobility restrictions during the COVID period. The COVID impact on mobility was modelled with separate dummy variables for the years 2020, 2021 and 2022. These dummy variables were included in the model for parameter T_i, as a fixed intercept and correlated random effect components, varying over travel purpose, age and gender. This ensures that our model captures the distinct mobility shifts of each year during the COVID period. Additionally, specific challenges in the e-bike market, such as delivery delays and production reductions due to chip shortages, have been particularly significant in the Netherlands due to its high demand for e-bikes. To account for these influences, we integrated the impact with time-location parameter T_i, by shifting this parameter with time delays as derived from the available e-bike sales data. By comparing the projected e-bike sales with the actual sales figures (BOVAG, 2023), we observed discrepancies. Based on this comparison, we quantified the delay in the growth curve to be a lag of 0.11 years for 2020, 0.24 years for 2021, and a minor 0.02 years for 2022. This means for example in 2020 the e-bikes growth has been set back by approximately 11 % of a year (roughly 40 days) when compared to the ideal or expected growth curve. In simpler terms, if in an undisturbed scenario you'd expect a certain number of e-bikes to be adopted by the end of 2020, because of the delay, this target might only be achieved 40 days into 2021.

3.2. Data and data fit

The multilevel model was fitted to Dutch national travel survey data from 2013 to 2022. The Dutch national travel survey (OViN (2013–2017) and ODiN (2018–2022)) was used to predict future e-bike usage and travel behaviour. The annually conducted OViN/ODiN involves approximately 40,000–62,000 individuals (0.2 % of the Dutch population) and is representative of the daily mobility of the Dutch population. We used the R-package brms (Bürkner, 2017) to fit the data. Brms is an interface to the Hamiltonian Monte Carlo (HMC) method of the probabilistic programming language Stan (Stan Development Team, 2023). Model fit evaluation and comparison of model variants were done with the approximate leave-one-out cross-validation methodology of the R package loo (Vehtari et al., 2017).

In addition to the model parameters, the model specification contains a model component that models the accuracy of the observations, which is the direct e-bike share from survey OViN and ODiN. In the survey world, these types of models are referred to as "Generalized Variance Function", see for example (Berzofsky et al., 2015). The variance function consisted of a four component fixed-effects: an intercept, the gender factor, a monotonic function of age class with purpose and a (smoothing) spline function (s) over the variance of the direct share estimate. A multivariate t-distribution was used as the distribution type of the model residues. The number of degrees of freedom of the t-distribution was also estimated by the model.

3.3. Results and discussion

Our analysis suggests a marked growth in e-bike usage in the coming years. Notably, the COVID period seems to have accelerated the growth of e-bike share, effectively steepening the growth curve with the most significant impact observed in 2022. This indicates that the COVID period has had a nudging effect on e-bike adoption. From 2022 onwards, the e-bike's share of the total bicycle distance is projected to grow from 36 % to 45 % by 2028. While the overall cycling distance is anticipated to grow by 13 %, it is noteworthy that the distance covered by conventional bicycles is predicted to decrease by 4 %. On the other hand, the distance travelled by using e-bikes is expected to see a substantial increase of 43 %. Thus, the surge in e-bike usage is the predominant contributor to the projected growth in total cycling distance.

A closer examination reveals variations in e-bike growth curves across different age groups. By 2028, the e-bike distance share is projected to be approximately 30 % for the 12–17 age group and will be around 75 % for the oldest 70 + age group, approaching saturation level (see Fig. 1). For those aged 60 and over, in 2022 e-bike use has already overtaken conventional bicycles in terms of travel distance. Based on our projections, this transition is prognosticated to encapsulate those aged 50 and above by 2025. It is worth noting that e-bike share increases with age, with the 12–17 age group being a notable exception.

In our analysis of gender differences, a clear trend emerges. Women, across all age groups, consistently have higher e-bike shares than men. This difference is especially pronounced among older age groups, which also report a higher overall e-bike usage compared to younger counterparts as shown in Table 1. While it's a known phenomenon in the Netherlands for e-bikes to be particularly popular among women (KiM, 2023), the dynamics appear to be evolving. As seen in Table 1, men aged 30 and above are gradually closing the gap. Conversely, among younger age groups, the gap is widening, with women's e-bike shares growing faster than men's. An exception is noted in the 18–24 age group; starting from 2023, men are forecasted to overtake women in e-bike distance share. It's important to clarify that, in absolute terms, men generally cycle more than women. However, women in almost all age groups, except 18–24 age group, covered more e-bike distance and made more e-bike trips than men. This distinction underscores the nuanced popularity of e-bikes between genders.

E-bike growth curves vary across travel purposes as well. Leisure and commute-related trips exhibit the fastest increase in e-bike usage (see Fig. 2). However, the total cycling distance varies for different travel purposes; for instance, leisure travel has the highest cycling distance compared to other travel purposes. In Fig. 3, we delineate the projected growth trends for overall bicycle, conventional bicycle, and e-bike distances across various travel purposes. Leisure trips register the largest increase in e-bike distance, closely followed by commute trips. It's encouraging to note the total cycling distance is increasing fast for leisure and commuting purposes. It's worthwhile to investigate whether e-bikes are replacing modes of transport other than conventional bicycles, especially for these two purposes. This aspect will be further explored in our Study 2, where we will examine the substitution effects of e-bikes in greater detail.

Table 1
The differences of e-bike distance share of total cycling distance between women and men for all age groups, a positive percentage mean women have a higher e-bike share than men.

	Share differences between women and men			
Age groups	2019	2022	2025	2028
12–17	2.3 %	3.2 %	3.7 %	4.0 %
18–24	0.2 %	-0.3 %	-1.9 %	-2.1 %
25–29	6.5 %	8.7 %	9.9 %	10.5 %
30–39	5.4 %	5.9 %	3.5 %	3.9 %
40–49	9.2 %	10.5 %	9.2 %	10.2 %
50–59	14.4 %	15.2 %	13.2 %	13.9 %
60–64	18.9 %	19.5 %	17.3 %	17.7 %
65–69	11.4 %	11.0 %	7.8 %	7.8 %
70+	8.3 %	7.6 %	4.4 %	4.4 %

4. Study 2: E-bike substitution effects

In the previous section, we highlighted emerging e-bike trends and noted the variations among different user groups and purposes. This

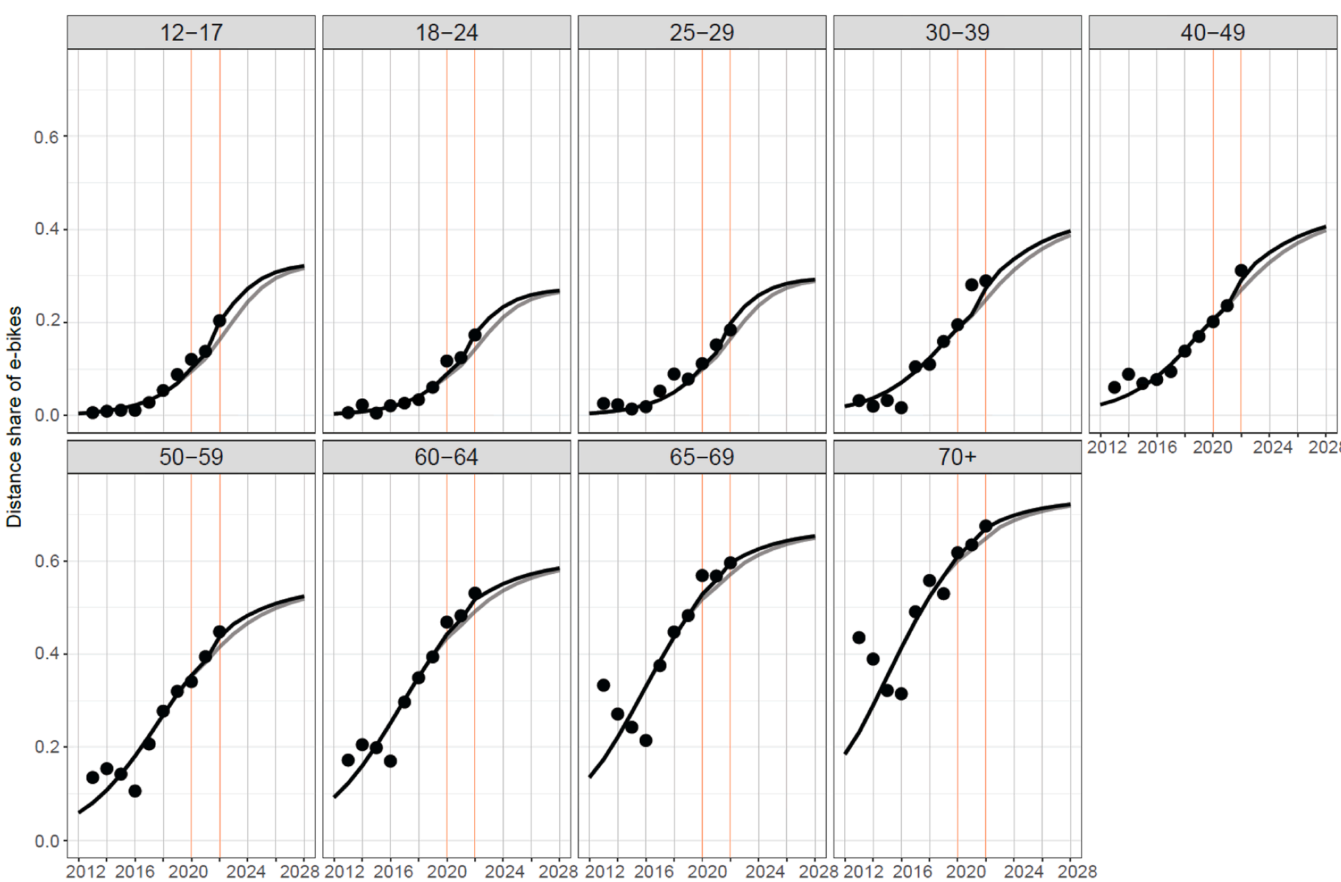

Fig. 1. E-bike distance share of total cycling distance for different age groups, black dots represent observed data points, the black line traces growth trends considering COVID and sales delay effects, while the grey line illustrates growth without the influence of COVID and delivery delays.

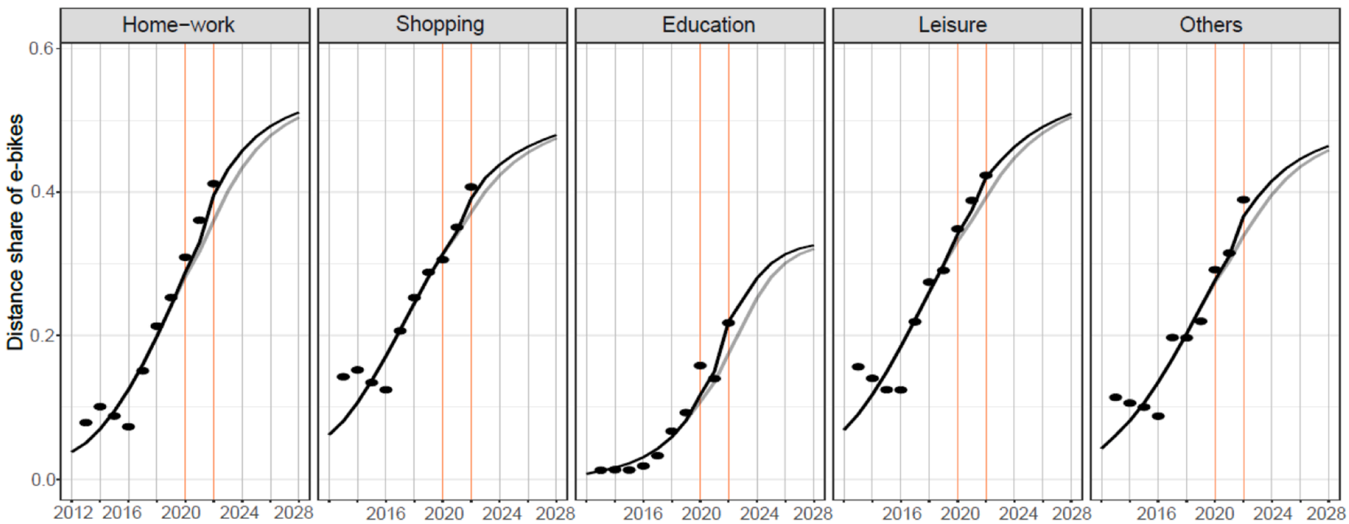

Fig. 2. E-bike distance share of total cycling distance for five travel purposes, black dots represent observed data points, the black line traces growth trends considering COVID and sales delay effects, while the grey line illustrates growth without the influence of COVID and delivery delays.

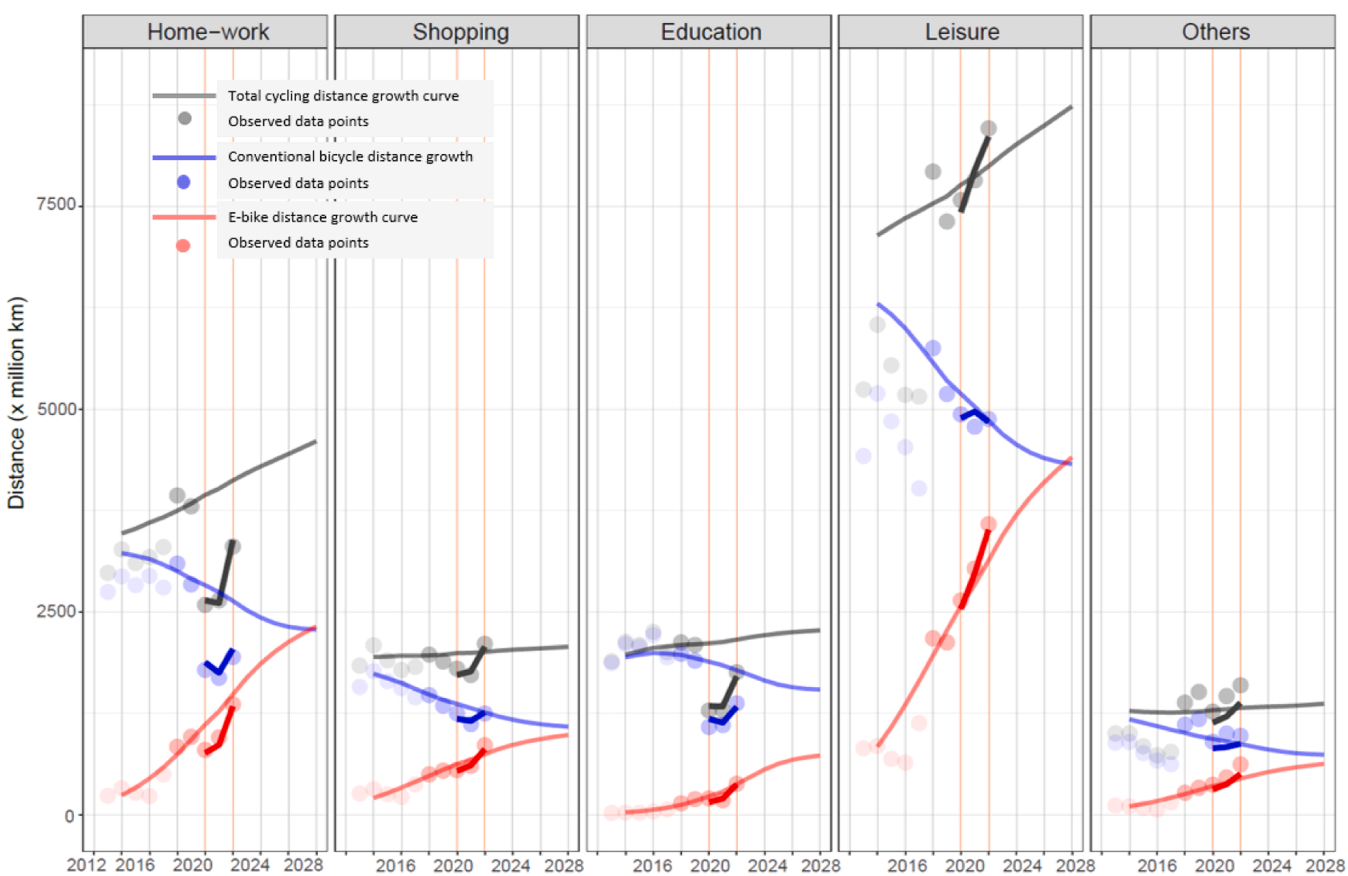

Fig. 3. Growth trends of overall bicycling, conventional bicycles, and e-bikes across various travel purposes.

section delineates our approach to predicting the e-bike substitution effect on a national scale for the five year period between 2019 and 2024.

4.1. Data and method

To evaluate the substitution effect of e-bikes on national mobility, we compared the modal split, travel distances, and trip frequencies of 2024 with those of 2019. We used the 2019 national survey as a baseline to forecast mobility patterns for 2024, isolating the impact of e-bike adoption. Specifically, we assumed that a subset of survey respondents would purchase e-bikes and adopt a new travel pattern accordingly, while the other respondents would maintain their current patterns of travel. This way allows us to control for other variables that might influence behaviour change. We chose 2019 as our reference year to exclude the disruptions caused by COVID lockdowns and mobility restrictions.

The initial step of this method is to collect people's intention to purchase an e-bike within the next five years. We then projected 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. We made this assumption because our e-bike adoption survey shows that future e-bike owners intend to use the e-bike in a similar manner to current owners.

4.1.1. Sources of data

The Netherlands Mobility Panel (MPN) is an annual household survey initiated in 2013 that captures the mobility behaviour of the Dutch population. Each year, individuals aged 12 and over from approximately 2000 households document their travel activities in a diary over three days, supplemented by various questionnaires (Hoogendoorn-Lanser et al., 2015). In 2021 edition, we administered an additional questionnaire to a sub-sample of the MPN to delve into e-bike adoption trends, exploring both motivations and barriers. Specifically, we gathered insights on participants' intentions to purchase an e-bike and their anticipated usage patterns. The 2021 panel consisted of feedback from 1046 e-bike owners and 1461 non-owners.

The Dutch National Travel Survey (ODiN 2018 and 2019), an annual survey with around 40,000 respondents (0.2 % of the Dutch population), has informed our predictions on future e-bike use and overall travel behaviours. This survey offers a comprehensive overview of daily mobility trends in the Netherlands. To capture these trends more accurately, especially for smaller sample groups like e-bike owners, we combined the 2018 and 2019 ODiN data to represent the year 2019.

While ODiN would be the preferred platform for gathering e-bike purchase intentions due to its direct representation on the national mobility, our lack of control over the ODiN survey means we cannot add specific queries related to e-bike adoption. As a result, we turned to the MPN for buying intentions and relied on ODiN to dissect travel behaviours.

4.1.2. Data integration and analysis

ODiN serves our purpose of measuring national-level mobility, while the MPN focuses on understanding behavioural shifts. While the MPN represents national population trends, it doesn't necessarily capture overall national mobility. As our research interest leans towards the impact of e-bikes on national mobility, it was essential to link the MPN to ODiN. The two datasets were connected through a matching process as shown in Fig. 4. This process aimed to connect the future adoption intentions sourced 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 who 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.

To further project 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 (de Haas and Huang, 2022). 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, 2010). Balancing complexity and practicality, we chose variables already proven effective in previous e-bike user group studies in the Netherlands (de Haas et al., 2021).

We chose pre-COVID data to predict future e-bike use, aiming to exclude the disruptions caused by lockdowns and mobility restrictions. However, our estimations may not encompass all determining factors, like demographic shifts, economic changes, or lasting post-COVID behavioural adjustments. Thus, our projections might not entirely represent the future e-bike landscape. It's also worth noting that our early 2021 survey could undervalue the intent to buy e-bikes, especially since both our first study and national sales data show a marked increase in e-bike interest during the COVID period. Yet, our first method can partially address this issue by validating the results. While we acknowledge that the future is uncertain, we ground our projections in the understanding that current behaviour is a robust indicator of near-term future behaviour. Thus, this method serves as a practical starting point, with room for future refinements.

4.2. Results and discussion

4.2.1. Data integration results

The quality of the estimation is depending on the matching method, in which we assume the travel behaviour of the non-owners with buying intention is the same as current e-bike owners who share the same socio-demographic profiles. A good match means that after matching the new owner group has the same socio-demographic distribution as the current owners. As seen in Table 2, we used gender, age, urbanity, education level, car ownership, and commute distance variables for matching. While incorporating a broader set of variables for matching might seem beneficial, we aimed to maintain the simplicity and clarity of our initial approach. This study serves as a practical starting point, and over-complicating the matching process might not guarantee improved match quality. Our results show a balancing matching since all socio-demographic variables' standardized mean differences are below 0.05 and Variance Ratios are close to 1 (see Appendix). However, the matching is based on covariate balance, which is the degree to which the distribution of covariates is similar across two groups. Therefore, we cannot have a perfect matching, but a balancing matching. In Table 2 we

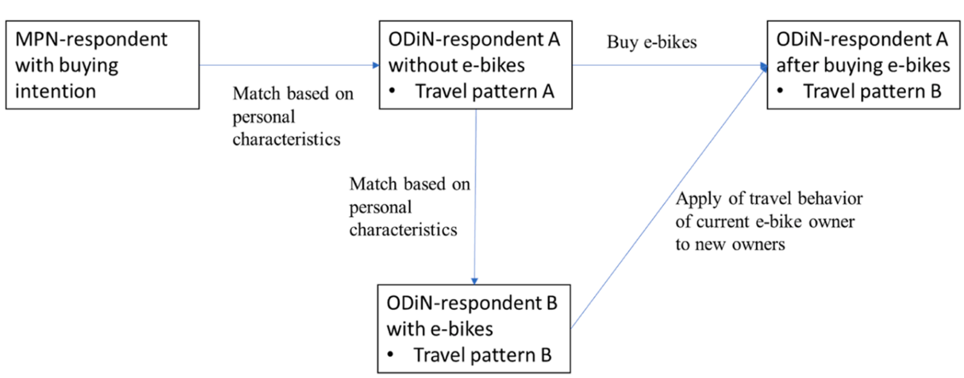

Fig. 4. Schematic representation calculation potential e-bike.

Table 2
Sample distribution differences before and after matching.

(unit: person)		Before matching	Before matching share	After matching	After matching share	Diff
Age classes	12–24	1508	9 %	1618	9 %	110
	25–35	2518	15 %	2330	14 %	-188
	35–45	2861	17 %	2880	17 %	19
	45–55	3774	22 %	3667	22 %	-107
	55–65	2956	17 %	3061	18 %	105
	65+	3422	20 %	3483	20 %	61
Gender	Man	8413	49 %	8423	49 %	10
	Woman	8626	51 %	8616	51 %	-10
Work situation	Fulltime	2135	13 %	2183	13 %	48
	Parttime	8244	48 %	8230	48 %	-14
	Student	1403	8 %	1425	8 %	22
	Others	5257	31 %	5201	31 %	-56
Education	Low	2990	18 %	3027	18 %	37
	Middle	6641	39 %	6624	39 %	-17
	High	7408	43 %	7388	43 %	-20
Urbanization	Highly urbanized	3833	22 %	3490	20 %	-343
	Strongly urbanized	5437	32 %	5799	34 %	362
	Moderately urbanized	2718	16 %	2908	17 %	190
	Slightly urbanized	4064	24 %	4019	24 %	-45
	Not urbanized	987	6 %	823	5 %	-164
Household car	No car	1695	10 %	1625	10 %	-70
	One car	10,301	60 %	10,382	61 %	81
	> 1 cars	5043	30 %	5032	30 %	-11
Driving license	Without driving license	2573	15 %	2570	15 %	-3
	With driving license	14,466	85 %	14,469	85 %	3
Commuting distance	No commuting Trips	11,244	66 %	11,637	68 %	393
	< = 5 km	1698	10 %	1459	9 %	-239
	5–15 km	1510	9 %	1857	11 %	347
	15–25 km	863	5 %	850	5 %	-13
	25–50 km	1073	6 %	847	5 %	-226
	> 50 km	651	4 %	389	2 %	-262
Number of trips (unit: trip)	Car (as driver)	19,464	38 %	18,918	37 %	-546
	Car (as passenger)	4109	8 %	4768	9 %	659
	Train	1611	3 %	969	2 %	-642
	BTM	2218	4 %	1240	2 %	-978
	Walking	9764	19 %	8105	16 %	-1659
	Conventional bicycle	12,097	24 %	5138	10 %	-6959
	E-bike	556	1 %	9920	20 %	9364
	Other	1651	3 %	1643	3 %	-8

can see the difference between non-owners and their matched e-bike owners based on ODiN2018/2019. We see there are always difference between before and after matching for each socio-demographic variable, which proves that it is not a perfect matching. However, the standardized mean of each variable was almost the same. If further analysis is carried out in subgroups, we may end up with unbalancing socio-demographic distributions in subgroups between new owners and current owners, especially when the subgroups end up with small samples. For example, the number of train and BTM trips in the new e-bike owner group was significantly different from the current e-bike owner group (see Table 2). This can be that the small sample of train and BTM travellers in both groups results in an unbalancing subgroup match. Therefore, cautious conclusions are further made for subgroups with small samples.

4.2.2. Expected e-bike use and substitution effects

The additional MPN survey was sent out to gather participants' intentions to buy e-bikes, along with other questions related to reasons for adoption and perceived barriers. Among the 1458 non-owners of e-bikes who responded, the MPN survey results indicate that 22 % of those aged 12 and older intend to adopt an e-bike (see Table 3). However, since it is a hypothetical question that participants require to answer, hypothetical bias may arise. One of that is that respondents' expressed preferences may differ from their actual behaviour under real economic circumstances (Hausman, 2012; Haghani et al., 2021). 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. The final estimate of new e-bikes is validated with national annual e-bike sale data (Stichting BOVAG-RAI Mobiliteit, 2022; BOVAG, 2023).

Table 3
Intention of e-bike adoption among non-owners.

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

We can project which subset of respondents in 2019 ODiN survey will become e-bikes owners by 2024 by linking ODiN with the assumed intentions in MPN as shown in Table 3. We assume that in 2024, this group of new e-bike owners will exhibit similar travel behaviours as existing e-bike owners in 2019, who have comparable socio-demographic backgrounds (detailed in Section 4.1). The remaining ODiN respondents are assumed to continue with their travel patterns as they were in 2019. This approach enables us to compare changes in travel distance, frequency, and modal split between 2019 and 2024 while controlling for other variables that may affect travel behaviour.

The analysis forecasts a moderate yet meaningful shift in mobility patterns by 2024. It is expected that e-bikes will account for 35 % of the total bicycle distance travelled, up from 23 % in 2019. Additionally, the average distance travelled per citizen per day by e-bike is expected to increase from 0.8 km to 1.3 km. Moreover, Table 4 indicates a notable reduction in the distances travelled using conventional bicycles and cars, indicating a shift towards e-bike usage.

The trip frequency share of each transport mode in different distance classes gives more insight into the expected e-bike impact between 2019 and 2024. As shown in Fig. 5, an increase in e-bike usage within each distance class corresponds directly to a decrease in conventional bicycle usage, suggesting e-bikes mainly replace conventional bicycle trips. However, for trips exceeding 7 km, the decrease of the conventional bicycle gets less pronounced and there is a notable decrease in the share of car driver trips, suggesting e-bike may replace some car trips over this distance. Additionally, short-distance BTM trips and long-distance train trips have both decreased. But due to the relatively 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. Still, our previous e-bike study (de Haas et al., 2021) found no evidence of e-bikes substituting car passenger or public transport trips. In conclusion, the results suggest an e-bike substitution effect on conventional bicycle and car use, but the substitution effect on public transport and car passenger trips needs more comprehensive data or corroborative studies before drawing solid conclusions.

A t-test analysis based on the average trip per person for each mode provides extra information about the significance of modal shift in car driver trips and conventional bicycle trips, which is shown in Table 5. Again, we see that effects on e-bike and conventional bicycle are significant, as well as the decrease in car as driver use. However, while the changes in the number of trips for train, BTM, and walking appear significant, we must exercise caution. Particularly for modes with relatively low usage, like public transport, interpreting these results requires careful consideration.

The development of e-bike ownership leads to different substitution effects for various purposes (see Fig. 6). A relatively high number of working people intend to buy an e-bike, which is projected to significantly impact commuter traffic. Nationally, we anticipate a 6.3 % decrease in the distance travelled by car for commuting by 2024 compared to 2019. This reduction is attributed to an overall increase in e-bike ownership, reflecting a shift toward using e-bikes for commuting. However, this figure is calculated without considering other factors that may also influence mode use for commuting, like demographic shifts, economic changes, or lasting post-COVID behavioural adjustments.

Car travel for shopping and social reasons is also expected to decrease due to the increase of e-bike owners. In contrast, distances covered as car passengers are projected to see a slight overall increase, particularly for shopping trips, with shopping car passenger distance increasing by 15.5 %. This increase might be tied to skewed matching results; an e-bike owner who frequently undertakes long car passenger trips might be overrepresented in future samples. Additionally. it's worth noting that, in comparison to the first study, there's an underestimation of e-bike usage regarding leisure and educational trips. This nuance should be factored into any conclusions drawn.

Table 4
Average distance (in km) per person per day and distance growth for each mode in five years, by T-test.

	National average distance in year 2024 (per person per day)	National average distance in year 2018/2019 (per person per day)	Average distance difference
Car (as driver)	19.2	19.7	-0.5 **
Car (as passenger)	6.6	6.5	0.0
Train	4.4	4.5	-0.1
BTM	1.2	1.2	0.0
Walking	0.9	0.9	0.0
Conventional bicycle	2.4	2.6	-0.2 ***
E-bike	1.3	0.8	0.5 ***
Other	2.0	2.1	-0.1
Total	37.9	38.3	-0.1

* significant at the 95 % level based on t-value.
** Significant at the 98 % level based on t-value.
*** Significant at the 99 % level based on t-value.

4.2.3. The generation effect

The generation effect in the context of e-bike usage refers to the creation of additional trips that were not occurring before the adoption of this mode of transport. Our analysis reveals a notable pattern as shown in Fig. 7: the adoption of e-bikes has led to an increase in the number of trips made for distances between 5 and 15 km, particularly for commuting to work and educational activities. Furthermore, there's a marked increase in leisure trips exceeding 15 km. Conversely, there's a decrease in the frequency of trips for shorter distances (below 5 km) and significantly longer distances (above 15 km), likely due to the convenience and efficiency e-bikes provide for intermediate travel distances.

Interestingly, despite these shifts in travel behaviour at the individual level, our national-level analysis indicates that the average number of trips per person per day has remained unchanged post the adoption of e-bikes, as demonstrated in Table 5. This suggests that while e-bikes influence the purpose and distance of travel, they may not necessarily increase the total number of trips per person on a nationwide scale.

We have also noticed from our MPN survey data that, in the absence of e-bikes, specific groups—particularly older individuals or those with physical limitations—might stop cycling or switch to car usage. E-bikes enable continued cycling among these key demographics, thereby preventing a shift to less environmentally-friendly modes, such as the car. This consideration of 'negative substitution' represents a significant, though indirect, substitution effect that contributes to environmental sustainability.

4.2.4. Comparison of two studies on e-bike usage

The two studies undertaken examine e-bike adoption from different perspectives. Study 1 primarily focuses on the projection of e-bike use trends, while Study 2 evaluates e-bike substitution effects, also yielding predictions for e-bike usage in 2024. A compelling feature of our dual-study approach is the opportunity for cross-validation. The 2024 e-bike usage predictions from Study 1 can be compared against those from Study 2, serving as a comparative benchmark.

Fig. 8 provides a visual comparison of the two studies' predictions on the share of e-bike distance over total cycling distance for 2024. Study 2's prediction in 2024 is more conservative than that of Study 1. This conservative estimate from Study 2 aligns with our anticipation, since the prediction only considered new e-bike owners but no other variables that impact mobility development. Moreover, we postulate the data from our early 2021 survey, which may have underestimated the intention to purchase e-bikes. This is proved by the accelerated e-bike adoption during the COVID era and the increase in e-bike usage during the COVID period as shown in Fig. 8.

A comparison of e-bike share projections by travel purpose presents some illuminating insights. Table 6 offers comparison of the e-bike share for 2024 derived from both methods. For all travel purposes, Study 2 reports a lower e-bike share than Study 1. This difference can be attributed to two primary factors. First, the impact of COVID on e-bike popularity. Study 2 may not have fully considered the impact of COVID on the rising popularity of e-bikes. During the COVID period, there was an increase in e-bike sales (BOVAG, 2023). This increase during the COVID period is not adequately captured in Study 2's projections, potentially leading to an underestimation of the actual e-bike adoption rate and the use of e-bike. Secondly, changes in e-bike usage patterns. The disparity in e-bike share estimates, especially for leisure and educational trips, suggests there may be a structural change in how e-bikes are being used. Recent findings in the Netherlands suggest that

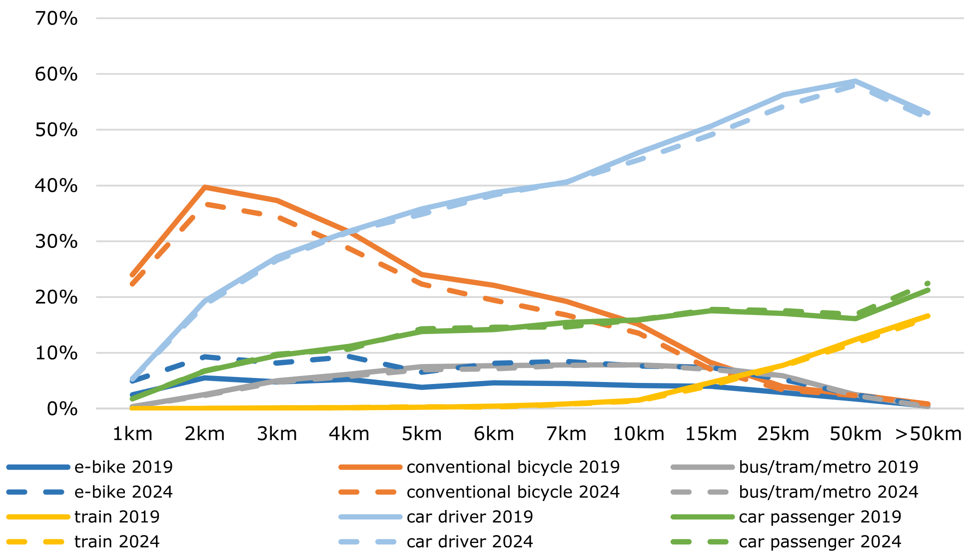

Fig. 5. The modal split classified per distance of 2019 and 2024.

Table 5
Average trips per person per day and trip growth for each mode in five years.

	National average trips in year 2024 (per person per day)	National average trips in year 2018/2019 (per person per day)	Average trips difference
Car (as driver)	1.00	1.02	-0.02 ***
Car (as passenger)	0.34	0.34	0.01
Train	0.09	0.09	0.00 *
BTM	0.13	0.14	-0.01 *
Walking	0.61	0.62	-0.01 *
Conventional bicycle	0.71	0.78	-0.07 ***
E-bike	0.22	0.12	0.09 ***
Other	0.10	0.10	0.00
Total	3.21	3.21	-0.01

** Significant at the 98 % level based on t-value.
* Significant at the 95 % level based on t-value.
*** Significant at the 99 % level based on t-value.

during the COVID period, e-bikes were used more frequently and for longer distances on leisure trips than in pre-COVID times (KiM, 2023). For educational trips, Study 1 noted a marked increase in e-bike usage among the 12–17 age group and a shift in gender trends within the 18–24 age group, pointing to a new trend in e-bike use among younger people. Study 2, not accounting for these demographic and behavioural changes, likely resulted in a lower e-bike share estimation for leisure and educational purposes.

5. Conclusions and future research

5.1. Conclusions

In this study, we delved into the growth patterns of the share of e-bike distance in the total bicycled distance in the Netherlands, focusing on its nuances across age, gender, and travel purposes. This is done by using the Richard growth curve within a hierarchical Bayesian framework, and the expected substitution effects of e-bikes on other modes of transport is analysed by using people's intention to buy an e-bike.

The COVID-19 period positively impacted the distance covered by e-bikes. It is expected to increase significantly between 2022 and 2028. Despite an anticipated 13 % growth in the overall cycling distance, conventional bicycles will see a 4 % decrease. On the flip side, e-bikes are estimated to experience a substantial 43 % growth in their travel distance. E-bike share growth curves exhibit distinct patterns across age demographics. By 2028, younger individuals will hold a 30 % e-bike distance share, while the 70+ will record a substantial 75 % share. For those aged 60 and over, in 2022 e-bike use has already overtaken conventional bicycles in terms of travel distance. This transition is prognosticated to encapsulate those aged 50 and above by 2025.

In gender-specific patterns, women displayed slightly higher e-bike usage than men (de Haas and Hamersma, 2020; Plazier et al., 2023). However, this gap is narrowing for older age groups while widening among younger demographics. Intriguingly, we perceive a potential for younger generations to chart a distinct trend compared to their older counterparts. A case in point is the 18–24 age group, where e-bike adoption is surging faster than in middle-aged groups, and men are embracing e-bikes more rapidly than women. Additionally, e-bike usage shows discernible variation based on the travel's purposes. Leisure and commuting trips show the most rapid incline in e-bike distance share, with leisure trips contributing the most to the total e-bike travelled distance.

E-bikes are expected to replace regular bicycles on shorter distances and car trips on longer distances. These expectations are based on our predictions, which focus on the increasing number of e-bike owners. We expect a significant increase in the use of e-bikes for commuting, which is likely to reduce car usage for distance longer than 7 kilometre. However, further research is needed to accurately measure this effect, as current studies rely on assumptions. Additionally, it's important to examine how increased e-bike adoption impacts public transport use. Current studies are limited by small sample sizes and may not fully capture this dynamic.

The potential 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 may lead to 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. The substitution of the normal bicycle for a certain group by e-bikes can also retain them cycling and prevent a shift from cycling to car use, particularly among older individuals or those with physical limitations. Moreover, with the increase in leisure trips and commuting using e-bikes, there's an opportunity to promote physical health and well-being among the population. If policymakers want to promote e-bike use, our previous study (de Haas and 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

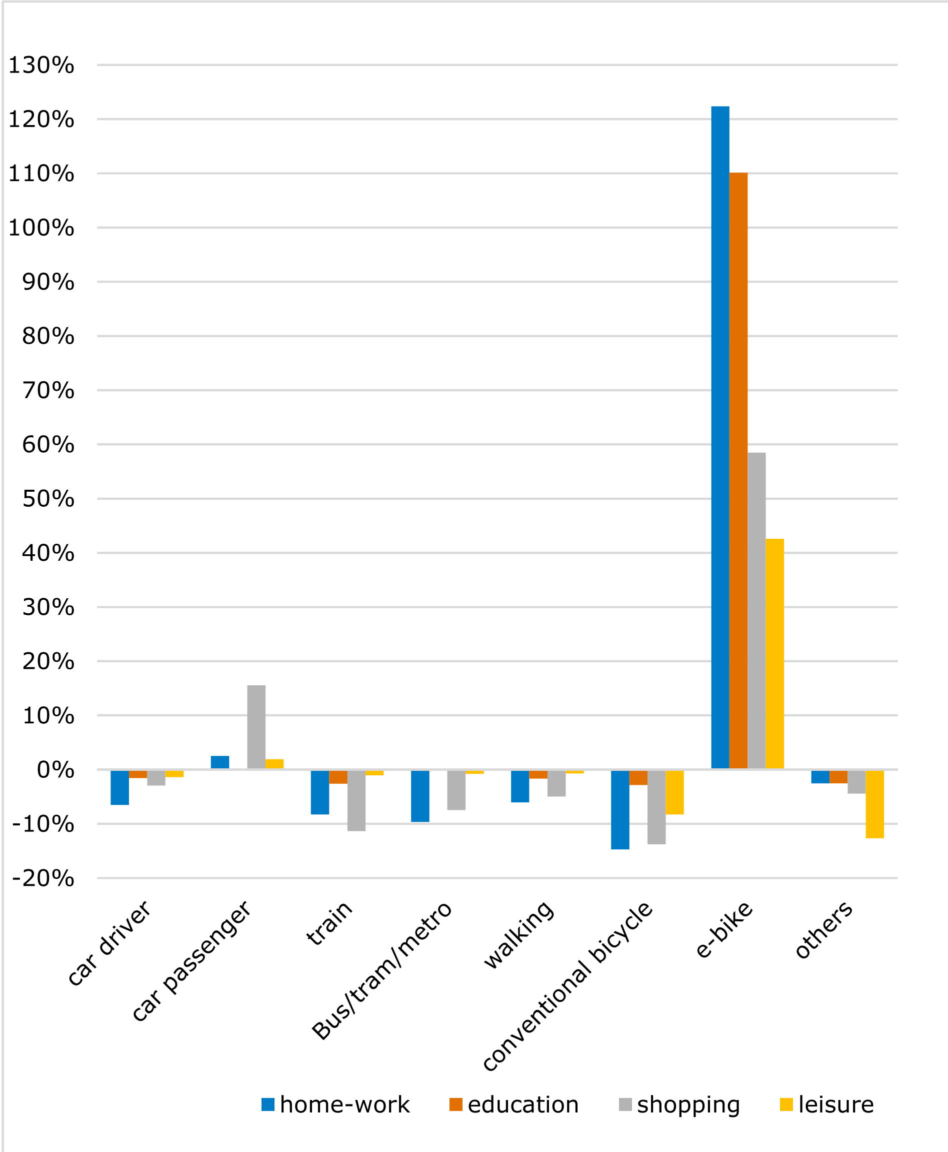

Fig. 6. Changes in distances covered per purpose per mode of transport between 2019 and 2024, based on projected e-bike adoption.

cycle paths with safer crossing points, increasing the cost of other modes of transport like cars and addressing barriers to commuting by e-bike such as improving facilities at the workplace (e.g., showers, changing areas, and providing secure bicycle parking).

Findings from the literature overview indicated that local context plays in a role in the substitution effects of the e-bike. Given the prominence of cycling in the Netherlands. our findings may be particularly relevant for countries with similar cycling cultures, such as Denmark and other Nordic countries.

5.2. Directions for future research

Our study, while providing insightful findings on the e-bike substitution and generation effects, presents certain limitations that pave the way for future research directions. A key limitation lies in our assumptions regarding new e-bike owners. We project their behaviour based on current e-bike users with similar demographic attributes. We also do not take into account other relevant factors that may affect e-bike usage, such as demographic and economic developments. Yet the dynamic nature of behavioural trends, influenced by events like the COVID-19 lockdown and work at home, shifting environmental attitudes, and changing local policies, can pose challenges to such assumptions. For a more nuanced understanding of e-bike usage trends, we recommend including these dynamic factors as matching variables in our method. Moreover, incorporating them as explanatory variables in the growth curve analysis can help us transition to a mixed model, offering refined insights. Additionally, we suggest the use of panel data to examine changes in individual behaviour following the adoption of e-bikes. This approach would allow for a more detailed analysis at the individual level, offering deeper insights into the e-bike substitution and generation effects.

Further, while our matching method provides practical insights, it encounters challenges, especially with smaller sample sizes for certain groups. For instance, our limited sample of train travellers who own e-bikes resulted in imbalanced subgroup matches. This highlights the potential of refining our approach, perhaps by subdividing samples into more homogeneous strata and then executing matches within these subsets, or include or exclude matching variables. Given our method's practical implications, it would also be valuable to test its efficacy in other countries or contexts where behavioural data is sparse. Such investigations would fortify the method's robustness across diverse scenarios.

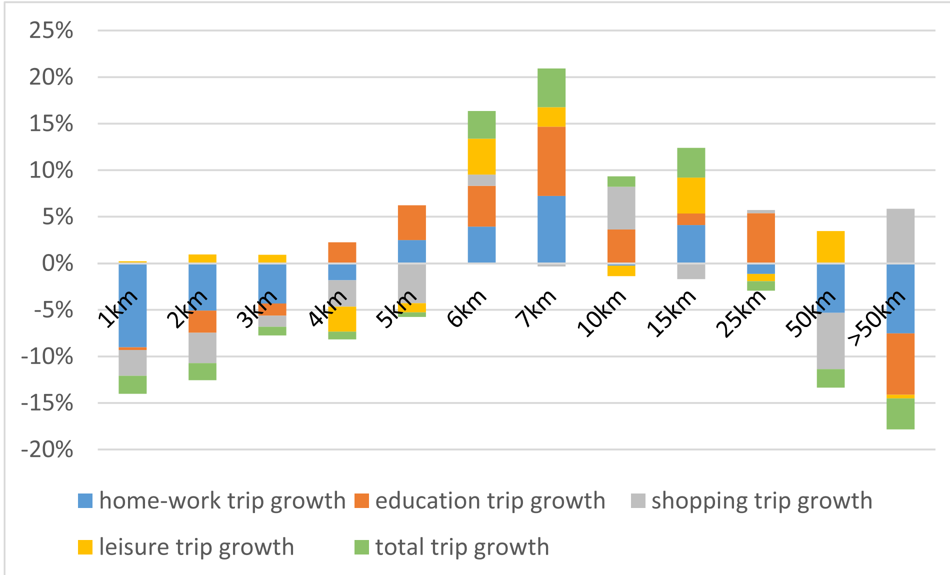

Fig. 7. Number of trips growth classified per distance of 2019 and 2024, based on projected e-bike adoption.

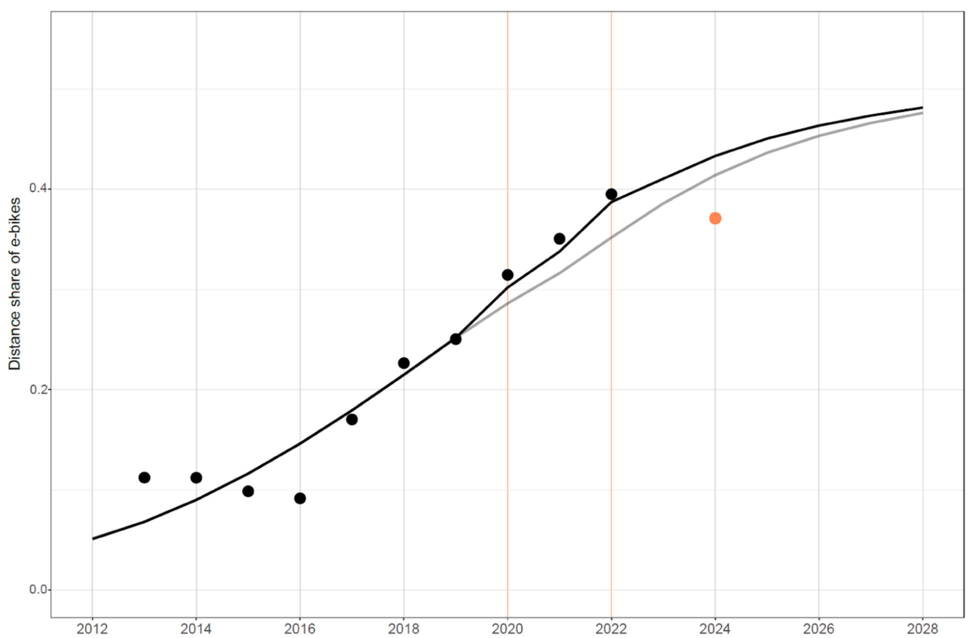

Fig. 8. Growth curve forecasting of e-bike's share in total bicycle distance, with the orange dot representing Study 1's results. Black dots represent observed data points, the black line traces growth trends considering COVID and sales delay effects, while the grey line illustrates growth without the influence of COVID and delivery delays.

Table 6
E-bike shares by travel purposes – a comparison from two studies.

Travel purpose	Study 1 (2024)	Study 2 (2024)
Home to work	46 %	44 %
Shopping/grocery	43 %	40 %
Education	28 %	14 %
Leisure	46 %	36 %
Others	41 %	

Another intriguing avenue stems from our observation of e-bike adoption patterns across demographics. Younger individuals seem to embrace e-bikes faster than the middle-aged cohort. Probing deeper into this trend, we must ask: Is this indicative of a lasting preference shift, or merely a passing phase? To unravel this, qualitative research methods, encompassing detailed surveys or interviews, can offer a lens into the motivations and challenges faced by different age brackets.

Lastly, our study's geographical limitation, centred on the Netherlands, underscores the need to explore e-bike patterns in broader contexts. Do our conclusions resonate globally, or are they emblematic of regional peculiarities? By extending our research to other countries, we can either validate the generalizability of our findings or spotlight distinct regional dynamics.

CRediT authorship contribution statement

Bingyuan Huang: Writing – review & editing, Writing – original draft, Visualization, Methodology, Formal analysis, Conceptualization.

Mathijs de Haas: Writing – review & editing, Project administration, Formal analysis. **Hans Wüst:** Writing – review & editing, Visualization, Methodology, Formal analysis.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgement

A previous version of this paper was presented at the 11th Symposium of the European Association for Research in Transportation (hEART 2023) in Zürich, Switzerland.

Appendix

We show in this appendix the matching results based on the method described in Study 2. As described in Study 2 and illustrated in Fig. 4, we estimated the e-bike use for the coming five years based on e-bike buying intention. Specifically, we projected e-bike use over five years by assuming that respondents with buying intentions would travel in the same way as current e-bike owners if they shared a similar socio-demographic background. To achieve this estimation, two matching steps, as outlined in Fig. 4, were necessary.

First, we linked respondents with e-bike buying intention in MPN to ODiN. The MPN contained buying intention information but was not suitable for calculating annual statistics for total Dutch mobility. Each MPN respondent with intention was matched with 31 ODiN respondents to ensure that the proportion of e-bike non-owners with intention in ODiN matched that in MPN after the matching process. We utilized data from the years 2018 and 2019 to estimate future e-bike use. Thus, the matching of MPN to ODiN was based on these two years. Tables A1 and A2 present the matching results for 2018 and 2019, respectively.

In the second step, we replaced each e-bike non-owner with buying intention in ODiN (obtained from the matching method in the first step) with a specific e-bike owner, provided they had a similar socio-demographic background and commuting distance. This step aimed to estimate the usage patterns of these prospective e-bike owners. The variables used for matching are presented in Tables A3 and A4. The number of e-bike non-owners with buying intentions is more than the number of e-bikers. Therefore, each e-biker may be used multiple times to match with different non-owners, which is carried out by the replacement methods. The matching results for 2018 and 2019 are shown in Tables A3 and A4 respectively.

The matching was based on covariate balance, which is the degree to which the distribution of covariates is similar across two groups. A good match means that after matching, the new owner group has the same socio-demographic distribution as the current owners. We used standardized mean differences and Variance Ratios to check the quality of the matching. For the first matching, 'Treated' denoted the ODiN group and 'Control' referred to the MPN group. For the second matching, 'Treated' is the ODiN e-bike non-owners with buying intention, and 'Control' is ODiN e-bikers. If each socio-demographic variable's standardized mean difference is below 0.05 and Variance Ratios is close to 1, we can conclude that we have a balancing match. The four tables show that the two matching steps all have balanced results.

Table A1
Summary of balance for matched MPN 2018 data and ODiN 2018

	Means treated	Means Control	Std. Mean Diff.	Var. ratio
Distance	0.0147	0.0147	0.0136	1.0002
Urbanization	2.6332	2.6087	0.0196	1.0197
Gender	1.4956	1.4973	-0.0035	1.0017
Age classes	47.3915	47.0469	0.0205	0.9669
Education	2.2857	2.2849	0.0011	0.9672
Work situation	2.5273	2.5251	0.0021	1.0016
Household car	1.1711	1.1697	0.0022	0.973
Driving license	0.8571	0.8571	0	

method: 31:1 nearest neighbor matching without replacement. distance: Mahalanobis. with propensity score. estimated with logistic regression. caliper: <distance> (0.001). number of obs.: 44723 (original), 18127 (matched (17560 Control, 567 Treated)).

Table A2
Summary of balance for matched MPN 2019 data and ODiN 2019

	Means treated	Means control	Std. Mean Diff.	Var. Ratio
Distance	0.0157	0.0157	0.0091	1.0013
Urbanization	2.6332	2.6116	0.0173	1.0017
Gender	1.4956	1.4976	-0.0041	1.0017
Age classes	47.3915	47.0544	0.02	0.9447
Education	2.2857	2.2875	-0.0025	0.9606
Work situation	2.5273	2.51	0.0164	1.0088
Household car	1.1711	1.1732	-0.0036	0.9742
Driving license	0.8571	0.8578	-0.0018	

method: 31:1 nearest neighbor matching without replacement. distance: Mahalanobis. with propensity score. estimated with logistic regression. caliper: <distance> (0.001). number of obs.: 41233 (original), 18144 (matched(17577 Control, 567 Treated)).

Table A3
Summary of balance for matched ODiN 2018 e-bike owners data and e-bike non-owners data

	Means treated	Means control	Std. Mean Diff.	Var. Ratio
Distance	0.5998	0.5984	0.008	1.0068
Urbanization	2.5915	2.5991	-0.0061	1.088
Gender	1.5027	1.4998	0.0057	0.9993
Age classes	48.4779	48.6414	-0.0096	0.9913
Education	2.2513	2.2484	0.0038	0.9993
Work situation	2.5839	2.5716	0.0116	0.992
Household car	1.1969	1.1998	-0.0048	1.0152
Driving license	0.8487	0.8487	0	
Commuting distance	4.8098	4.8448	-0.0192	1.0052

method: 1:1 nearest neighbor matching with replacement. distance: Mahalanobis. with propensity score. estimated with logistic regression. caliper: <distance> (0.045). number of obs.: 18267 (original), 12340 (matched (2503 Control, 9837 Treated)).

Table A4
Summary of balance for matched ODiN 2019 e-bike owners data and e-bike non-owners data

	Means treated	Means control	Std. Mean Diff.	Var. Ratio
Distance	0.5734	0.5724	0.0068	1.0053
Urbanization	2.5863	2.5749	0.0092	1.0584
Gender	1.5051	1.5067	-0.0032	0.9995
Age classes	48.6566	48.7508	-0.0055	0.9911
Education	2.2553	2.2527	0.0036	0.9891
Work situation	2.5748	2.571	0.0035	1.0093
Household car	1.1988	1.2035	-0.0078	1.0228
Driving license	0.8491	0.8494	-0.0009	
Commuting distance	4.8474	4.8728	-0.014	1.0052

method: 1:1 nearest neighbor matching with replacement. distance: Mahalanobis. with propensity score. estimated with logistic regression. caliper: <distance> (0.042). number of obs.: 19008 (original), 12516 (matched(2658 Control, 9858 Treated).

References

Arning, L., Silva, C., Kaths, H., 2023. Review of current practice and research on E-bikes in transport models. Transp. Res. Rec. 2677 (12), 436–448. https://doi.org/10.1177/03611981231168848.

Berzofsky, M.E., Heller, D., Williams, R., 2015. Developing generalized variance functions for estimates of recidivism rates. JSM Proc. Surv. Res. Methods Sect. 1736–1772. In: http://www.asasrms.org/Proceedings/y2015/files/234025.pdf.

Boonstra, H.J., van den Brakel, J., Das, S., 2021. Multilevel time series modelling of mobility trends in the Netherlands for small domains. J. R. Stat. Soc. Ser. A: Stat. Soc. 184 (3), 985–1007. https://doi.org/10.1111/rssa.12700.

BOVAG, 2023. Aandeel e-bikes in fietsverkoop blijft stijgen in 2022. From ⟨https://www.bovag.nl/nieuws/aandeel-e-bikes-in-fietsverkoop-blijft-stijgen-in⟩.

Bürkner, P.C., Charpentier, E., 2020. Modelling monotonic effects of ordinal predictors in Bayesian regression models. Br. J. Math. Stat. Psychol. 73 (3), 420–451. https://doi.org/10.1111/bmsp.12195.

Bürkner, P.C., 2017. Advanced Bayesian multilevel modeling with the R package brms. arXiv preprint arXiv:1705.11123. https://doi.org/10.48550/arXiv.1705.11123.

CONEBI, 2021. 2021 European Bicycle Industry and Market Profile. CONEBI-Confederation of the European Bicycle Industry.

de Haas, M., Hamersma, M.. Fietsfeiten: nieuwe inzichten. 2500 EX Den Haag, Kennisinstituut voor Mobiliteitsbeleid (KiM). https://www.kimnet.nl/publicaties/brochures/2020/10/12/fietsfeiten-nieuwe-inzichten.

de Haas, M., Huang, B., 2022. Aanschaf en gebruik van de elektrische fiets, achtergrondrapport. 2500 EX Den Haag, Kennisinstituut voor Mobiliteitsbeleid (KiM).https://www.kimnet.nl/publicaties/publicaties/2022/09/15/aanschaf-en-gebruik-van-de-elektrische-fiets.

Cherry, C.R., Yang, H., Jones, L.R., He, M., 2016. Dynamics of electric bike ownership and use in Kunming, China. Transp. Policy 45, 127–135. https://doi.org/10.1016/j.tranpol.2015.09.007.

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.

Fishman, E., Cherry, C., 2016. E-bikes in the mainstream: reviewing a decade of research. Transp. Rev. 36 (1), 72–91. https://doi.org/10.1080/01441647.2015.1069907.

fka Andersson, A.S., Adell, E., Hiselius, L.W., 2021. What is the substitution effect of e-bikes? A randomised controlled trial. Transp. Res. Part D: Transp. Environ. 90, 102648. https://doi.org/10.1016/j.trd.2020.102648.

Gan, Y., Lu, Z., Cai, H., Wang, M., He, X., Przesmitzki, S., 2020. Future private car stock in China: current growth pattern and effects of car sales restriction. Mitig. Adapt. Strateg. Glob. Change 25, 289–306. https://doi.org/10.1007/s11027-019-09868-3.

Geroski, P.A., 2000. Models of technology diffusion. Res. Policy 29 (4–5), 603–625. https://doi.org/10.1016/S0048-7333(99)00092-X.

Haghani, M., Bliemer, M.C., Rose, J.M., Oppewal, H., Lancsar, E., 2021. Hypothetical bias in stated choice experiments: Part II. Conceptualisation of external validity, sources and explanations of bias and effectiveness of mitigation methods. J. Choice Model. 41, 100322. https://doi.org/10.1016/j.jocm.2021.100322.

Hallberg, M., Rasmussen, T.K., Rich, J., 2021. Modelling the impact of cycle superhighways and electric bicycles. Transp. Res. Part A: Policy Pract. 149, 397–418. https://doi.org/10.1016/j.tra.2021.04.015.

Hausman, J., 2012. Contingent valuation: from dubious to hopeless. J. Econ. Perspect. 26 (4), 43–56. https://doi.org/10.1257/jep.26.4.43.

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

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

Jong, G.D., Fox, J., Daly, A., Pieters, M., Smit, R., 2004. Comparison of car ownership models. Transp. Rev. 24 (4), 379–408. https://doi.org/10.1080/0144164032000138733.

KiM, 2023. Mobiliteitsbeeld 2023. Kennisinstituut voor Mobiliteitsbeleid (KiM).https://www.kimnet.nl/publicaties/publicaties/2023/11/14/mobiliteitsbeeld-2023.

Kroesen, M., 2017. To what extent do e-bikes substitute travel by other modes? Evidence from the Netherlands. Transp. Res. Part D: Transp. Environ. 53, 377–387. https://doi.org/10.1016/j.trd.2017.04.036.

Lu, H., Ma, H., Sun, Z., Wang, J., 2017. Analysis and prediction on vehicle ownership based on an improved stochastic Gompertz diffusion process. J. Adv. Transp. 2017. https://doi.org/10.1155/2017/4013875.

Plazier, P., Weitkamp, G., van den Berg, A., 2023. E-bikes in rural areas: current and potential users in the Netherlands. Transportation 50 (4), 1449–1470. https://doi.org/10.1007/s11116-022-10283-y.

Plazier, P.A., 2018. Power to the Pedals: Perspectives on the Potential of E-bike Mobility for Sustainable and Active Transport Systems. University of Groningen.

Rao, J.N., Molina, I., 2015. Small Area Estimation. John Wiley & Sons, Hoboken.

Rayaprolu, H.S., Llorca, C., Moeckel, R., 2020. Impact of bicycle highways on commuter mode choice: a scenario analysis. Environ. Plan. B: Urban Anal. City Sci. 47 (4), 662–677. https://doi.org/10.1177/2399808318797334.

Rérat, P., 2021. The rise of the e-bike: towards an extension of the practice of cycling? Mobilities 16 (3), 423–439. https://doi.org/10.1080/17450101.2021.1897236.

Rogers, E.M., Singhal, A., Quinlan, M.M., 2014. Diffusion of innovations. An Integrated Approach to Communication Theory and Research. Routledge, pp. 432–448.

Simsekoglu, Ö., Klöckner, C., 2019. Factors related to the intention to buy an e-bike: a survey study from Norway. Transp. Res. Part F: Traffic Psychol. Behav. 60, 573–581. https://doi.org/10.1016/j.trf.2018.11.008.

Stan Development Team, 2023. Stan Modeling Language: User's Guide and Reference Manual, Version 2.33.

Stichting BOVAG-RAI Mobiliteit, 2022. Mobiliteit in Cijfers Tweewielers 2022–2023. Stichting BOVAG-RAI Mobiliteit, Amsterdam.

Stuart, E.A., 2010. Matching methods for causal inference: a review and a look forward. Stat. Sci.: A Rev. J. Inst. Math. Stat. 25 (1), 1. https://doi.org/10.1214/09-STS313.
Sun, Q., Feng, T., Kemperman, A., Spahn, A., 2020. Modal shift implications of e-bike use in the Netherlands: moving towards sustainability? Transp. Res. Part D: Transp. Environ. 78 https://doi.org/10.1016/j.trd.2019.102202.
Tjørve, E., Tjørve, K.M., 2010. A unified approach to the Richards-model family for use in growth analyses: why we need only two model forms. J. Theor. Biol. 267 (3), 417–425. https://doi.org/10.1016/j.jtbi.2010.09.008.
Vehtari, A., Gelman, A., Gabry, J., 2017. Practical Bayesian model evaluation using leave-one-out cross-validation and WAIC. Stat. Comput. 27, 1413–1432. https://doi.org/10.1007/s11222-016-9696-4.
Vrána, J., Remeš, V., Matysioková, B., Tjørve, K.M., Tjørve, E., 2019. Choosing the right sigmoid growth function using the unified-models approach. Ibis 161 (1), 13–26. https://doi.org/10.1111/ibi.12592.
Wolf, A., Seebauer, S., 2014. Technology adoption of electric bicycles: a survey among early adopters. Transp. Res. Part A: Policy Pract. 69, 196–211. https://doi.org/10.1016/j.tra.2014.08.007.