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E-bike ownership and use determinants and their trends in the Netherlands

Yushan Zhang *, Dena Kasraian, Pieter van Wesemael

Eindhoven University of Technology, the Netherlands

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ABSTRACT

The global e-bike market has been growing significantly in recent years and is expected to keep expanding in the coming years. While many scholars have looked into e-bikes from operations management and user perspectives, the roles of different socio-demographic and built environment factors in e-bike ownership and use are less studied. Especially, how this role changes over time is rarely investigated. This paper explores i) how e-bike ownership and use have changed over time in the Netherlands, ii) how e-bike ownership and use relate to different socio-economic and built environment determinants, and iii) how these relationships have changed over time. Ten binary multinomial logistic regression models are developed to analyze how various determinants affect e-bike ownership and e-bike use respectively, using eight years of travel data from the Dutch national mobility surveys (2014–2021). The results show that e-bike ownership and use in the Netherlands have experienced consistent growth over time. Throughout the study period, e-bikes are becoming more widely adopted across diverse socio-demographic groups, and the influence of household size, household income, age, gender and education on e-bike ownership and use is decreasing. Interestingly, the penetration of e-bikes in non-urban areas is growing. Future urban and transport policies are recommended to take advantage of the growing e-bike adoption and the shifts in the socio-demographics and the residential locations of its adopters.

1. Introduction

In recent years, the worldwide e-bike market has been growing significantly, especially in Europe and China (Sun et al., 2023). The popularity of e-bikes comes from their beneficial characteristics for the environment and health (Jones et al., 2016). Moreover, they provide additional pedaling support and lead to higher speeds with the same or less effort. This overcomes the distance and effort barriers compared to conventional bikes, thereby enhancing the comfort and efficiency of cycling experience.

A rapidly expanding strand of literature on e-bikes mirrors its significant growth and popularity (Zhang et al., 2023). Most of the studies are from Europe, Asia, and North America (Fishman and Cherry, 2016). *E*-bikes in China are powered solely by an electric motor, while some e-bikes do not have pedals installed (Sun et al., 2023). E-bikes in North America are bike-style e-bikes, which can get up to 500 W motor power and can reach a speed of 32 km/h (Fishman and Cherry, 2016). This study focuses on the Netherlands, where e-bikes are also bike-style, only deliver power when pedaling, and have a motor power that is limited to 250 W and a maximum speed of 25 km/h (ANWB, 2023; Rijksoverheid, 2024a). *E*-bikes share the same infrastructure as conventional bicycles, including the use of dedicated bicycle paths. People are not allowed to hold electrical devices while riding e-bikes (Rijksoverheid, 2024b). This paper specifically focuses on privately owned e-bikes. Other types of e-bikes, including those with different definitions and shared e-bikes, are beyond the scope of this study.

Several policies are released in the Netherlands to promote e-bikes for commuting. At the national level, the Dutch government wants to encourage people to use e-bikes for commuting via their employers. The tax scheme is changed to encourage employers to build appropriate facilities for e-bikes, such as charging stations, and allow their employees to benefit from company bikes, including e-bikes, to encourage people to use their e-bikes for commuting (Rijksoverheid, 2024c). Complementary policies exist at some municipalities as well. For example, the municipality of Nijmegen launched a campaign to encourage people to commute with their e-bikes by offering an e-bike for two weeks free of charge (Heijendaal, 2024). The cycling incentive program from the province of North Brabant provides financial compensation per kilometer of cycling (de Kruijf et al., 2024).

Within this growing body of research, an important topic is exploring and modeling the ownership and use of e-bikes (Philips et al., 2024). *E*-bikes are used for recreational use and utilitarian travel, including

* Corresponding author.
E-mail addresses: y.zhang7@tue.nl (Y. Zhang), d.kasraian@tue.nl (D. Kasraian), p.j.v.v.wesemael@tue.nl (P. van Wesemael).

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commuting and shopping. People choose e-bikes as a commute mode, because of their ability to travel a longer distance (Dill and Rose, 2012; Müller et al., 2020). In recent years, more and more people own e-bikes and use them as substitutes for conventional bicycles, public transport, and cars (Kroesen, 2017). A better understanding of the determinants of e-bike ownership and use, and their influence over time are needed to guide future actions to encourage e-bike use, in attempts to further establish low-carbon commuting habits.

Given the increasing popularity of e-bikes, it is interesting to investigate whether there have been shifts in e-bike user demographics and the influence of the built environment on usage patterns, while taking into account the COVID-19 pandemic years. Q. Sun et al. (2020) and de Haas et al. (2021) investigate the e-bike users in the Netherlands, however, these analyses are constrained by data that predates 2017. Consequently, there is a significant gap in understanding the developing e-bike ownership and use patterns with more recent data to capture potential changes including the pandemic time period.

Furthermore, destination accessibility is one of the recognized built environment determinants of travel behavior (Cervero and Kockelman, 1997; Ewing and Cervero, 2010). Similar to other transport modes, the number of opportunities that can be reached by e-bikes and the cost of reaching them, such as travel time, are crucial factors in e-bike ownership and use. The built environment characteristics at destination locations can also affect individuals' mode choice (Higuera-Mendieta et al., 2021). However, the role of destination accessibility and the built environment characteristics at destination locations in e-bike ownership and use, has been rarely studied, and how this role has developed over time remains unexplored.

In short, the existing literature lacks a long-term overview of e-bike ownership and use and an understanding of their determinants over the years and whether they have been significantly changing. To address this gap, we aim to answer three questions in the Dutch context: What are the trends in e-bike ownership and use? What are the determinants of e-bike ownership and use? Are the roles of different determinants changing over time?

This paper thus conducts an empirical analysis of the dynamic relationship between e-bike ownership and e-bike use in the Netherlands and their determinants from 2014 to 2021 using descriptive, cross-sectional and time series analyses. The determinants include socio-demographic factors and built environment characteristics at both home and destination locations. This paper focuses on the work commute (henceforth referred to as commute). This constitutes the lion's share of commuting (Ettema et al., 2012) and is specifically relevant in light of more recent Dutch mobility transition policies that aim to increase the use of e-bikes for travel to work.

The remainder of this paper is structured as follows. Section 2 reviews existing literature on e-bike ownership and use. Section 3 shows the data, methodology and modal specifications. Section 4 presents the model results. Section 5 discusses the findings compared to previous studies. Section 6 concludes the important findings, limitations, and future research directions.

2. Literature review

Many researchers have investigated the rise of e-bikes. Studies reveal that e-bikes could overcome some of the barriers faced by conventional cyclists, thus empowering more people (young students, women, couples with children, and people with physical limitations) to cycle (Dill and Rose, 2012; Melia and Bartle, 2021; Rérat, 2021). Additionally, the rise of e-bikes could reduce the use of public transport, conventional bikes, and cars, for different travel purposes, including work commuting, leisure and shopping (Bigazzi and Wong, 2020; Melia and Bartle, 2021; Plazier et al., 2017).

Table 1 summarizes the socio-demographic and built environment determinants of e-bike ownership identified in existing literature. The scope is limited to literature focusing on electric bikes that provide power while pedaling, with a maximum motor capacity of 250 watts and a maximum speed of 25 km per hour. Other types of two-wheelers that exceed 25 km per hour, do not require pedaling, or any other special mopeds, such as those without a saddle (RDW, 2024) and shared e-bikes, are not included.

Table 1
Studies on e-bike ownership determinants.

Variable	Study	Country	Result
Socio-demographic			
Gender	(de Haas et al., 2021)	NL	*E*-bike users are predominantly female
	(Kroesen, 2017)	NL	E-bike ownership increases with being female
	(Melia and Bartle, 2021)	UK	Women are more likely to buy an e-bike
Age	(de Haas et al., 2021)	NL	*E*-bike users have a relatively high average age. Pensioners (generally >65) constitute a high share of total e-bike users
	(Kroesen, 2017)	NL	E-bike ownership increases with age
	(Kohlrautz and Kuhnimhof, 2024)	DE	E-bike ownership increases untill the age of 40, then rises more rapidly until the age of 70, and then declines again
Number of household members	(Kroesen, 2017)	NL	E-bike ownership decreases with household size
Household income	(Kroesen, 2017)	NL	E-bike ownership increases with household income
	(Kohlrautz and Kuhnimhof, 2024)	DE	Higher household economic status is associated with higher e-bike ownership
Education level	(Kroesen, 2017)	NL	E-bike ownership decreases with education level
Car ownership	(Kroesen, 2017)	NL	E-bike ownership has no strong relation with car ownership.
Built Environment			
Residential density	(Kroesen, 2017)	NL	Negative
Living plage (Metropole, city, middle size town)	(Kohlrautz and Kuhnimhof, 2024)	DE	*E*-bike ownership is negatively correlated to living in metropolises and cities

Notes: NL: The Netherlands; UK: United Kingdom; DE: Germany.

The topic of using e-bikes for work commuting has received much attention from scholars. Studies have found that e-bikes are used for work commuting as replacements for other modes, including the car (Plazier et al., 2017), public transport (Weinert et al., 2007) and the conventional bike (Melia and Bartle, 2021).

Table 2 summarizes the studies about e-bike use and the identified effects of socio-demographic, built environment factors, and travel distance. For instance, de Kruijf et al. (2018) found that the likelihood of using the e-bike decreased as work commuting distance increased.

E-bike ownership and use can be affected by socio-demographic factors at both the individual (e.g. gender, age, work location) and the household level (e.g. household income, household composition), as well as built environment characteristics. Many studies have investigated the role of gender in e-bike ownership. It is generally found that females are more likely to own/use e-bikes. This can be attributed to the fact that the pedal assistance from an e-bike enables and empowers women to cycle (Latz, 2021; Van Cauwenberg et al., 2019; Wild et al., 2021). Several studies conducted before 2022 found that e-bikes are more likely to be owned and used by older people (de Haas et al., 2021; de Kruijf et al., 2018; de Kruijf et al., 2021; Kroesen, 2017). However, recent evidence from Kohlrautz and Kuhnimhof (2024) reveals a non-linear relationship, with e-bike ownership increasing up to the age of 70 before declining among older age groups. A possible reason is that the

Table 2
Studies on e-bike use determinants.

Variable	Study	Country	Result
Socio-demographic			
Gender	(de Kruijf et al., 2018)	NL	Men use e-bikes more often than women
	(Philips et al., 2024)	UK	Women ride less e-bike milage than men
	(Plazier et al., 2023)	NL	Women are more likely to use e-bikes
Age (25–39, 40–49, 50–64)	(de Kruijf et al., 2018)	NL	E-bikes are more popular among older age groups
Age (25–39, 40–49, 50–65)	(de Kruijf et al., 2021)	NL	The youngest group of participants (aged 25 to 39 years old) had a significantly lower probability of e-cycling compared to the age group 50 to 64-year-olds,
Education	(Plazier et al., 2023)	NL	Higher education is negatively related to e-bike use
Household composition (single, single parent, couple without children, couple with children)	(de Kruijf et al., 2018)	NL	Shift to e-cycling is affected by household composition
	(Melia and Bartle, 2021)	UK	People who mostly or always commute by e-bikes are more likely to have children in the households
	(Plazier et al., 2023)	NL	Households without children are more likely to use e-bikes
Household income (<3 k, 3 k–4 k, >4 k per month)	(de Kruijf et al., 2021)	NL	A low household income (<3000 euros a month) of participants (compared to high incomes) had a significantly higher probability of e-cycling
Car ownership	(de Kruijf et al., 2021)	NL	Participants with two or more cars in their household were less likely to e-cycle
	(Melia and Bartle, 2021)	UK	People who mostly or always commute by e-bikes are more likely to have no car in the household.
	(Plazier et al., 2023)	NL	Car ownership is positively related to e-bike use
Built Environment			
Degree of urbanity	(Plazier et al., 2023)	NL	The degree of urbanity is not significant in e-bike use
Commute distance (0–5, 5–10, 10–15, 15–20, >20 km)	(de Kruijf et al., 2018)	NL	The likelihood of e-bike use decreases as commuting distance increases (highest likelihood for 0-5 km)
Commute distance (0–5, 5–10, 10–15, 15–20, >20 km)	(de Kruijf et al., 2021)	NL	Commute distance of more than 5 km has a positive effect on choosing e-bikes for commuting
Commute duration (<30, 30–60, >60 min)	(Rérat, 2021)	CH	*E*-bikers cover on average longer commuting distances than bike
Travel distance (0–5, 5–10, 10–15, 15–20, >20 km)	(Q. Sun et al., 2020)	NL	Most e-bike trips fall between the range of 5–15 km
Commute distance (0–15, >15 km)	(Plazier et al., 2023)	NL	Travel less than 15 km are more likely to use e-bikes

Notes: NL: The Netherlands; UK: United Kingdom; CH: Switzerland.

relationship between age and e-bike ownership and use is evolving as e-bikes become more accessible and accepted across a broader range of age groups. In addition, Huang et al. (2024) find that in the Netherlands, e-bikes are more popular among women and the gender gap in using e-bikes is gradually closing.

Furthermore, the findings indicate that e-bike use and its determinants are highly dependent on the local contexts. Thus, studies from different countries with different socio-cultural and geographical characteristics could draw different conclusions. For example, Melia and Bartle (2021) find that in the United Kingdom people with kids at home are more likely to commute with e-bikes, while Plazier et al. (2017) shows that in the Netherlands households without children are more likely to use e-bikes. This point is also emphasized by Hu et al. (2021) who note that e-bike use may differ between geographical contexts.

Few studies have investigated the role of built environment determinants in e-bike ownership and use. Kohlrautz and Kuhnimhof (2024) find that e-bike ownership is negatively correlated to living in metropolises and cities. Kroesen (2017) concludes that e-bike ownership decreases with residential density, which serves as a proxy for the degree of urbanity. However, in a more recent study, Plazier et al. (2023) find that the degree of urbanity is not significant in e-bike use. Next to the difference in context, a possible reason for this shift is that the effect of the degree of urbanity has diminished over time.

Existing studies present varying findings regarding the determinants of e-bike ownership and use. While the role of the degree of urbanity at home locations has been examined, other built environment factors, such as destination accessibility and the characteristics of the built environment at work locations, remain unexplored. To the best of our knowledge, no study has yet investigated how the influence of these built environment factors evolves over time. Furthermore, the period of the COVID-19 pandemic, which likely affected transport modalities due to social distancing measures and increased preference for outdoor activities, remains notably absent from recent studies. Incorporating data from this period could provide invaluable insights into the dynamics of e-bike utilization in response to public health crises and changing urban lifestyles, most notably more active healthy lifestyles. Studying this in the context of the Netherlands with its wide variety of urban environment types from the rural to urban spectrum accompanied by a mature cycling infrastructure with high density and coverage of cycle paths, makes more sense given its advanced (e-) cycling stimulation policies, built environment cycling design and planning intervention strategies and its mature cycling practices. This paper adds to the above literature by empirically investigating the role of the built environment on e-bike ownership and use (in terms of commute mode choice) within the Dutch context while controlling for the roles of commute distance and various socio-demographics.

Building on findings from the literature, it is suspected that the determinants of e-bike ownership and use may change over time. Firstly, the effect of age on e-bike use might decrease over time. While early adopters of e-bikes were predominantly older individuals, a broader range of age groups has increasingly embraced e-bikes, likely due to their growing integration into mainstream mobility. Secondly, the effect of gender on e-bike use might diminish over time. Earlier studies found that women were more likely to use e-bikes; however, this gender-based disparity appears to be narrowing, potentially due to the increasing normalization of e-bike use across demographics. Thirdly, the effect of the degree of urbanity on e-bike ownership and use might decrease over time. While previous research indicated that e-bike ownership is negatively associated with high residential density areas, this effect may be weakening as travel behaviors evolve. Furthermore, similar shifts have been observed in other transport modes, where socio-demographic and built environment determinants change over time (Cubells et al., 2020; Kasraian et al., 2020). Based on these insights, two hypotheses are proposed: (1) the relationship between socio-demographic factors (e.g., age, gender) and e-bike ownership and use changes over time. (2) the relationship between built environment characteristics (e.g., degree of urbanity) and e-bike ownership and use changes over time.

3. Data and method

3.1. Data

This paper analyzes Dutch travel data during an eight-year period (2014–2021). The data are obtained from OViN (Onderzoek Verplaatsingen in Nederland) and ODiN (Onderweg in Nederland). OViN is an annual Dutch national travel survey of approximately 40,000 individuals (0.2 % of the Dutch population) until 2017 (Statistics Netherlands, 2017), and ODiN is the continuation of OViN. Weighting factors are used to make the survey data representative of the entire Dutch population. The pooled sample consists of 1,270,288 trips over 3848 4-digit postcodes (PC4), with an average area of 8.6 km^2, nested in 387 municipalities, covering the entire Netherlands. For this analysis, only commute trips from home location by walking, car, e-bike, bike and public transport are included, resulting in 91,150 one-way trips from home to work locations, as shown in Table 3.

The Dutch travel survey is conducted online, via telephone or face-to-face. The participants are asked to fill in a one-day travel diary, their personal characteristics (e.g. gender, age, education), household characteristics (e.g. household composition and income), and trip characteristics (e.g. departure and destination locations and travel mode). The sample is selected randomly from the population register of Statistics Netherlands and is accompanied by weighting factors to make it representative of the Dutch population. These weighting factors are calculated according to the background characteristics relevant to travel behavior, such as age, gender, income, urbanity and vehicle ownership. The sample has three weighting factors: one for person level, one for trip level and one for household level. In this analysis, household level weights are applied in the e-bike ownership models where household sociodemographic variables are used, such as household composition. Trip level weights are applied in the e-bike use models where person level sociodemographic variables are included, such as age and income.

Table 4 shows an overview of the variables used in the analysis, their definition, sources and descriptives of the pooled sample. The dependent variables, including e-bike ownership and commute mode, and the socio-demographic independent variables are collected by OViN (Statistics Netherlands, 2014–2017) and ODiN (Statistics Netherlands, 2018–2021).

The built environment variables including the degree of urbanity and distance to amenities such as general practice and school at the PC4 level. In the absence of data on the work location of all household members, we estimate the model based on the commute distance and work location built environment characteristic of one of the household members that is known to us. For the degree of urbanity, data are collected by OViN (Statistics Netherlands, 2014–2017) and ODiN (Statistics Netherlands, 2018–2021). For the distance to amenities, open data from StatisticsNetherlands (2017) for each period is used. For home and work locations the centroids of the PC4 areas are used.

To enlarge the sample size and reduce the number of models, data were grouped into 4 consecutive periods, each consisting of 2 years (Table 5). The COVID years constitute the 4th period (years 2020 and

Table 3
Number of commute trips and individuals, Dutch national travel surveys (2014–2021) Number of trips.

Number of trips					
Walk	Car	E-bike	Bike	PT	Total
(3.6 %) 3320	(53.2 %) 48,467	(4.4 %) 3978	(21.5 %) 19,595	(21.5 %) 15,790	91,150
Number of households					
E-bike owner (20.9 %) 16,678		Not e-bike owner (79.1 %) 63,238			Total 79,916

Table 4
Source of variables and description for the pooled sample.

Variable	Description	Mean or %	S. D.	Source
Dependent variables				
E-bike ownership	0: no e-bike;	83.2 %		OViN (Statistics Netherlands, 2014–2017) and ODiN (Statistics Netherlands, 2018–2021)
	1: at least one e-bike	16.8 %		
E-bike use (travel mode)	0: not e-bike;	95.9 %		
	1: e-bike	4.1 %		
Socio-demographic				
Person level				
Age	0: 0–29;	25.7 %		OViN (Statistics Netherlands, 2014–2017) and ODiN (Statistics Netherlands, 2018–2021)
	1: 30–39;	19.5 %		
	2: 40–49;	22.0 %		
	3: 50–59;	22.7 %		
	4: >60	10.1 %		
Gender	0: male;	55.8 %		
	1: female	44.2 %		
Employment	0: work less than 30 h per week;	33.5 %		
	1: work more than 30 h per week	66.5 %		
Education	0: education less than MBO (HAVO, VMBO, etc.);	62.1 %		
	1: education higher than MBO and equivalent (MBO, HBO, WO, Master, etc.)	37.9 %		
Household level				
Household composition	0: single	17.8 %		
	1: couple	26.0 %		
	2: couple with child (ren)	46.8 %		
	3: other	9.4 %		
Household size	0: total number of person in the household is more than 3	32.8 %		
	1: total number of person in the household is 3 or less	67.2 %		
Car ownership	0: no car in the household;	15.8 %		
	1: at least one car in the household	84.2 %		
Moped ownership	0: no moped in the household;	95.0 %		
	1: at least one moped in the household	5.0 %		
Motorcycle ownership	0: no motorcycle in the household;	93.7 %		
	1: at least one motorcycle in the household	6.3 %		
Household income	0: gross income first 50 % group	63.1 %		
	1: gross income second 50 % group	36.9 %		
Built environment				

(continued on next page)

Table 4 (*continued*)

Variable	Description	Mean or %	S. D.	Source
Degree of urbanity (PC4 level)	1: very highly urban (>2.5 k addresses per km^2);	23.2 %		OViN (Statistics Netherlands, 2014–2017) and ODiN (Statistics Netherlands, 2018–2021)
	2: highly urban (1.5 k–2.5 k addresses per km^2);	29.9 %		
	3: moderately urban (1 k–1.5 k addresses per km^2);	17.0 %		
	4: low urban (500-1 k addresses per km^2);	21.6 %		
	5: non-urban(<500 addresses per km^2)	8.4 %		
Potential accessibility 15 min	Number of people that can be reached by e-bike within 15 min at PC4 level	1.9	2.1	Own calculation using ArcGIS
Dist. to GP practice	Network dist. to the nearest GP practice [km]	1.8	1.5	Statistics Netherlands (2014–2021)
Dist. to supermarket	Network dist. to the nearest supermarket [km]	1.7	1.5	Statistics Netherlands (2014–2021)
Dist. to day care center	Network dist. to the nearest day care center [km]	1.2	1.1	Statistics Netherlands (2014–2021)
Dist. to school	Network dist. to the nearest school [km]	1.1	1.0	Statistics Netherlands (2014–2021)
Commute distance				
Commute distance from home to work location	1: 0-5 km;	32.6 %		OViN (Statistics Netherlands, 2014–2017) and ODiN (Statistics Netherlands, 2018–2021)
	2: 5-10 km;	16.8 %		
	3: 10-15 km;	10.4 %		
	4: 15-20 km;	7.9 %		
	5: more than 20 km	32.3 %		

Notes: PC4: four-digit postal code.
MBO: secondary vocational education in the Dutch education system; HAVO: senior general secondary education; VMBO: pre-vocational secondary education; HBO: higher professional education; WO: scientific/academic education (Rijksoverheid, 2022).
Moped: Vehicle with a maximum speed of not more than 45 km/h, equipped with an internal combustion engine, with a cylinder capacity of not more than 50 cm^3 (according to Dutch law) or an electric motor with a power not exceeding 4 KW (StatisticsNetherlands, 2024a).
Motorcycle: Motor vehicle on two or three wheels, with or without sidecar, fitted with a combustion engine with a cylinder capacity of 50 cm^3 or more (StatisticsNetherlands, 2024b).

2021). From 2014 to 2017, the e-bike ownership data was collected by asking the participants how many e-bikes their household had. Participants could choose from options of zero up to nine e-bikes or more. Since 2018, the participants were only asked if they have at least one e-bike at home. For consistency, the e-bike ownership variable is coded as no e-bike and at least one e-bike.

E-bike ownership data is collected at the household level, while the e-bike use is at the trip level. The use data is collected by asking the participants about their main mode of transport based on the longest leg of the journey in terms of distance. The e-bike use variable is defined as:

$$e-bike\ use = \begin{cases} 1, if\ participant\ choose\ e-bike \\ 0, if\ participant\ chose\ other\ modes \end{cases} \quad (1)$$

Fig. 1. (a-c) shows the spatial distribution of three key variables across the Netherlands at the municipal level: (a) degree of urbanity, (b) e-bike ownership, and (c) share of e-bike commute trips from all commute trips. Fig. 1.a shows the degree of urbanity using the year of 2017 as an example. Fig. 1.b represents the proportion of e-bike owner households (possessing at least one e-bike) from the total number of households for each municipality in quintiles. Fig. 1.c illustrates the percentage of e-bike trips from the total number of trips in quintiles. Comparing Fig. 1.a and Fig. 1.b shows that areas with a lower degree of urbanity have higher e-bike ownership. For instance, the provinces of Friesland, Groningen, and Drenthe in the north of the Netherlands have a lower degree of urbanity (mainly non-urban areas), but higher e-bike ownership.

Table 5
Cross-sectional and pooled model overview.

Model	Time frame (year)	Sample size (households/trips)	Variable type
Cross-sectional models			
Goal: To identify the role of socio-demographic (SD) and built environment (BE) determinants in each period (e-bike use models also control for commute distance (CD))			
Example: Does income play a role in e-bike ownership in period 1 (2014–15)?			
E-bike ownership model (household level)			
Model 1	P1: 2014–2015	16,126 households	SD, BE
Model 2	P2: 2016–2017	15,030 households	SD, BE
Model 3	P3: 2018–2019	27,183 households	SD, BE
Model 4	P4: 2020–2021	21,577 households	SD,BE
E-bike use model (trip level)			
Model 5	P1: 2014–2015	16,126 trips	SD, BE, CD
Model 6	P2: 2016–2017	15,030 trips	SD, BE, CD
Model 7	P3: 2018–2019	34,680 trips	SD, BE, CD
Model 8	P4: 2020–2021	25,314 trips	SD, BE, CD
Pooled models with time interactions			
Goal: To identify if the role of determinants has significantly changed between periods			
Example: Has the effect of income significantly changed between period 1 (2014–15) and period 4 (2020−21)?			
E-bike ownership model (household level)			
Model 9	P1–4: 2014–2021	79,916 households	SD, BE, interaction terms
E-bike use model (trip level)			
Model 10	P1–4: 2014–2021	91,150 trips	SD, BE, CD, interaction terms

Notes: BE = Built Environment; SD = Socio-demographic; CD = Commute Distance; P = period.

The degree of urbanity for both home and work locations at PC4 level is included in the analysis. In most studies, only the built environment at home location is considered, however, work location built environment characteristics, such as urban or rural, can substantially affect commuting behaviors. Analyzing the degree of urbanity of work locations can provide valuable insights into the complexities of commuting and e-bike use, allowing for more targeted and effective urban planning and transportation policies.

Fig. 2 and Fig. 3 demonstrate the growth of e-bike ownership and use in the Netherlands. Throughout the period under investigation, both e-bike ownership and use exhibit upward trends. Compared to the growth pattern of e-bike ownership, e-bike use shows a more dynamic trajectory. Regions may experience increases in e-bike use during certain periods, which can later decline, indicating a vibrant and fluctuating area of growth. This phenomenon can be attributed to the fact that households once having acquired an e-bike, are most likely to keep it for a while. However, the decision to commute by e-bike remains dynamic, considering the flexibility of choosing other modes based on varying daily circumstances or preferences. Fig. 4 shows the changes in e-bike ownership and use from the period 2014–2015 to the period 2020–2021. It clearly shows that the majority of PC4 areas exhibit an increase in e-bike ownership. However, the increase in e-bike use is not that pronounced.

The potential accessibility measure is a gravity-based indicator of a PC4's potential access to opportunities, proxied by population counts in destination PC4s, by e-bike. It is computed by an equation using population counts in destination PC4s and a function of travel time between

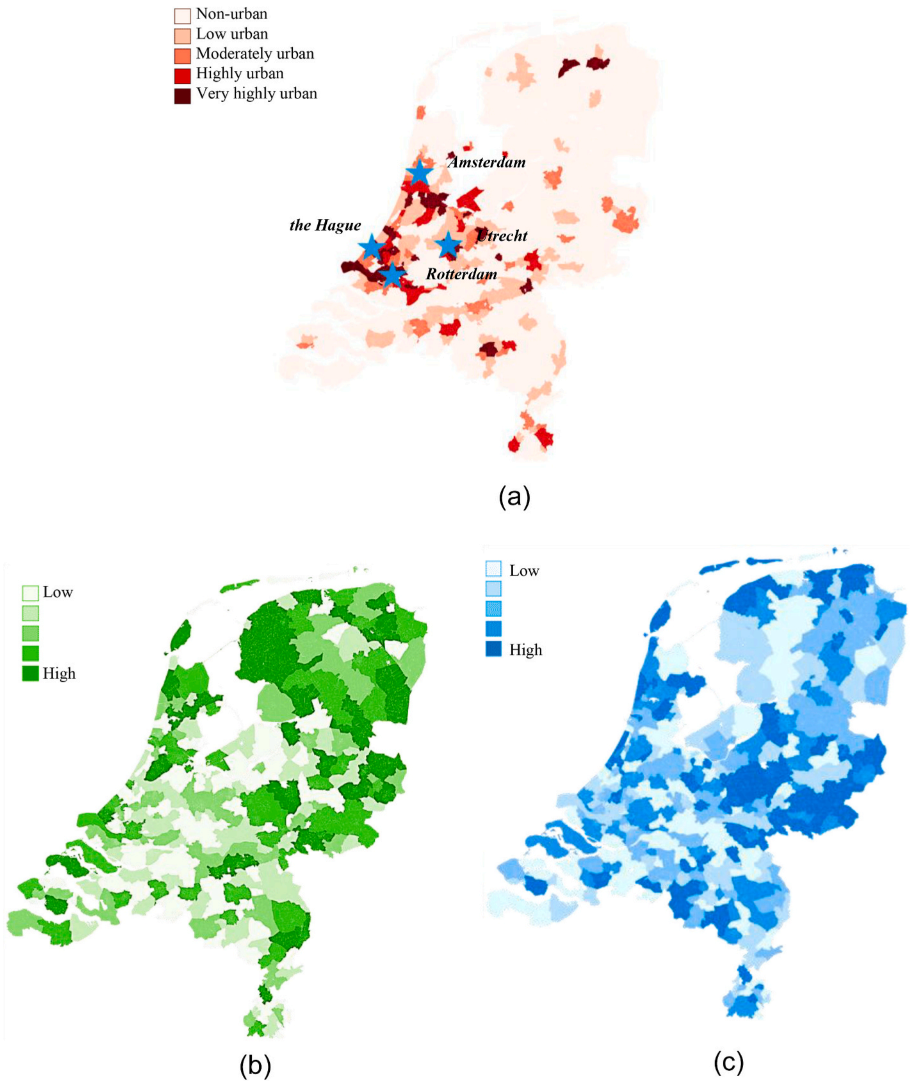

Fig. 1. (a) degree of urbanity in 2017, (b) share of e-bike owner households from all households at the municipal level (quintiles) and (c) share of e-bike trips from all trips at the municipal level (quintiles).

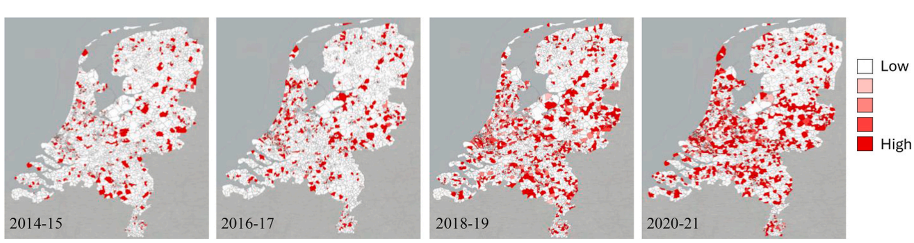

Fig. 2. Share of e-bike owner households from all households at the PC4 level (2014–2021).

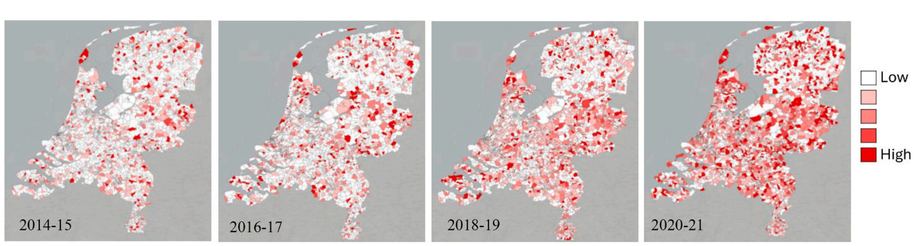

Fig. 3. Share of e-bike trips from all trips at the PC4 level (2014–2021).

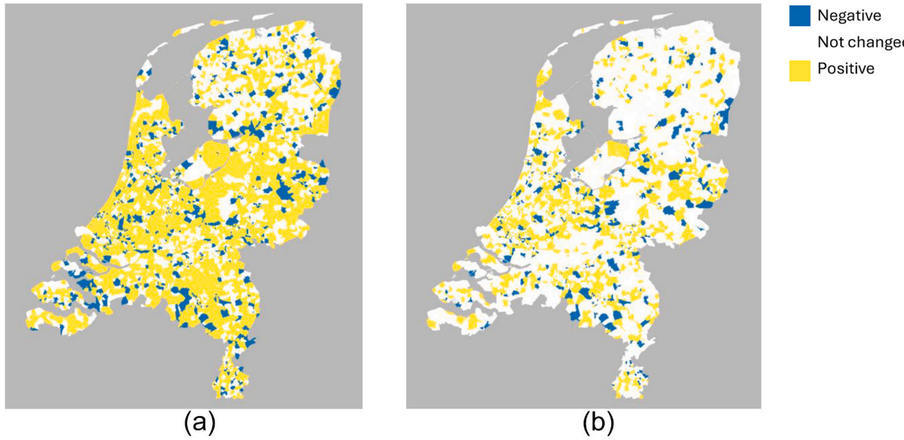

Fig. 4. (a) Changes in the share of e-bike owner household from all households at the PC4 level from the period 2014–15 to the period 2020–21 (b) Changes in the share of e-bike trips from all trips at the PC4 level from the period 2014–15 to the period 2020–21.

the centroids of origin PC4 *i* and destination PC4 *j*, as following:

$$potential\ access_i = \sum_{j=1}^{n} population_j {}^* e^{-\beta travel\ time_{i,j}} \tag{2}$$

where β is the distance decay parameter set to 0.093. This is calculated based on an exponential function with the empirical commuting data in the Netherlands (Muhammad et al., 2008); The travel time is calculated based on the network distance and the average e-bike travel speed of 15 km/h on the road network.

It is argued that the relative potential accessibility rather than the absolute potential accessibility is a better predictor of travel behavior (Handy and Niemeier, 1997; Kasraian et al., 2020). The relative potential accessibility is calculated by a population weighted average potential accessibility indicator based on Koopmans et al. (2012):

$$relative\ potential\ access_i = potential\ access_i / \overline{potential\ access} \tag{3}$$

$$\overline{\text{potential access}} = \frac{1}{\sum_{i=1}^{k} \text{population}_i} \sum_{i=1}^{k} (\text{population}_i {}^* \text{population access}_i) \tag{4}$$

The potential accessibility calculated above captures the accessibility of each post code to the population reached within 15 min of e-cycling.

3.2. Methodology and modal specifications

Logistic regression models are well suited for describing and testing hypotheses about relationships between an outcome variable, including categorical and binary variables, and a set of predictor variables (Peng et al., 2002). Here, we estimate ten binary logistic models to analyze e-bike ownership and e-bike use in the Netherlands over an eight-year timespan.

3.2.1. Cross-sectional analysis

E-bike use has undergone a significant change in recent years. The cross-sectional analysis identifies e-bike ownership and use patterns among different population groups in areas with different built environments in different years.

Separate regression models are estimated for each period: model 1 to model 4 for ownership and model 5 to model 8 for e-bike use.

Models 1–4 analyze the relationship between e-bike ownership and the socio-demographic and built environment variables.

$$\boldsymbol{O} = \beta_{10} + \boldsymbol{BE}_{1h}\beta_{11} + \boldsymbol{SD}_1\beta_{12} \tag{5}$$

where *O* is e-bike ownership at the household level; *BE* is a vector of built environment variables corresponding to e-bike ownership; *h* refers to home location; *SD* is a vector of socio-demographic variables.

Model 5 to model 8 estimate e-bike use by built environment and socio-demographic determinants, while controlling for the role of commute distance (CD).

$$\boldsymbol{U} = \beta_{20} + \boldsymbol{BE}_{2h}\beta_{21} + \boldsymbol{BE}_{2w}\beta_{22} + \boldsymbol{SD}_2\beta_{23} + \boldsymbol{CD}\beta_{24} \tag{6}$$

where *U* is the e-bike use; *BE* is a vector of built environment variables corresponding to e-bike use; *h* and *w* refer to home location and work location; *CD* is the commute distance.

3.2.2. Time series analysis

Cross-sectional analyses identify e-bike ownership and use patterns among different population groups in areas with different built environments in different years. However, they cannot identify if the role of determinants has significantly changed between different periods (Kamruzzaman et al., 2020). To compare coefficients of the factors among different periods, pooled binary regression models with year dummies and interaction terms are used.

Model 9 estimates e-bike ownership by socio-demographic and built environment determinants together with the interaction terms with the year dummies.

$$\boldsymbol{O} = \beta_{30} + \boldsymbol{BE}_{3h}\beta_{31} + \boldsymbol{SD}_3\beta_{32} + \boldsymbol{YEAR}\beta_{33} + \boldsymbol{BE}_{3w} {}^* \boldsymbol{YEAR}\beta_{34} + \boldsymbol{SD}_3 {}^* \boldsymbol{YEAR}\beta_{35} \tag{7}$$

where Year is the year dummies; * is for the interaction terms.

Model 10 estimates e-bike ownership by socio-demographic and built environment determinants together with the interaction terms with the year dummies.

$$\mathbf{U} = \beta_{40} + \mathbf{BE}_{4h}\beta_{41} + \mathbf{BE}_{4w}\beta_{42} + \mathbf{SD}_4\beta_{43} + \mathbf{CD}\beta_{44} + \mathbf{YEAR}\beta_{45} + \mathbf{BE}_{4h} {}^* \mathbf{YEAR}\beta_{46}$$

$$+ \boldsymbol{BE}_{4w} {}^* \boldsymbol{YEAR}\beta_{47} + \boldsymbol{SD}_4 {}^* \boldsymbol{YEAR}\beta_{48} + \boldsymbol{CD} {}^* \boldsymbol{YEAR}\beta_{49} \tag{8}$$

Time interactions with each predictor are estimated for periods 2–4, each compared with period 1. The interactions for each determinant with each time point are basically the effects of that variable at that time point compared to the base time point, which is the 2014–15 period in this case. The interaction terms show whether and to what extent each determinant's impact varies over time. The sums of coefficients for the main and interaction effects for each time can be interpreted as the 'period-specific' coefficients.

Table 5 summarizes the time frames, sample sizes and variable types in the ten models. The e-bike ownership models are at the household level while the e-bike use models are at the trip level. For built environment variables, the value for each period corresponding to the model period is used, for instance, in model 1 the built environment value of the period of 2014–15 is used. The e-bike ownership and use models test Hypotheses (1) and (2), which posit that the effect of socio-demographic and built environment factors change over time.

To examine the robustness of the model results, sensitivity analyses are performed by incorporating the private bike ownership and shared bike service availability into the models. Previous studies find that travelers' mode choice can be influenced by private bike ownership (Hasnine et al., 2018; Liu et al., 2018) and shared bike services (Fan et al., 2019; Ma et al., 2020). As a result, these two factors are included in the analysis. The results are compared with those from the original models to ensure consistency and robustness of the conclusions. By comparing the results of these modified models with the original models, it is assessed whether the inclusion of these variables led to any significant changes in the relationships between e-bike ownership and its determinants, which helps confirm the stability and reliability of the conclusions drawn from the original models.

4. Results

4.1. Descriptive analysis

Table 6 presents the characteristics of the socio-demographic and built environment variables used in the e-bike ownership and use models over the time periods.

Fig. 5.a shows the share of e-bike owner households in the Netherlands has witnessed a steady growth over time. An accelerated growth can be observed between the 2018–2019 period and the 2020–2021 period related to the e-bike growth in the COVID period, which is also found by Huang et al. (2024). Fig. 5.b and 5.c demonstrate the share of household e-bike ownership by household car ownership and income. The share of e-bike owner households with at least one car is higher and growing faster compared to those with no car. In order to see the role of car ownership on e-bike ownership while controlling other factors, multi-variate regression analysis is needed, which will be discussed in Section 4.2. Households with higher income exhibit a higher share of e-bike ownership than those with lower income. Both household types are increasingly owning more e-bikes over time, and at more or less the same rate. The share of e-bike ownership across all five degrees of urbanity has been growing over the years, with non-urban areas having the highest share and growth rate, and very highly urban areas having the lowest share and growth rate.

Fig. 5.e shows the trends in e-bike use in the Netherlands, including the share of e-bike trips among all trips and trips from e-bike owners only. Similar to the growth in e-bike ownership, e-bike use among all trips has accelerated growth in the last period of the study (the COVID period). While e-bike use is growing, the share of e-bike trips is lower and has a slower growth rate compared to the e-bike ownership. When considering trips made exclusively by e-bike owners, the percentage of e-bike trips is approximately 20 %, and it has remained relatively stable throughout the study period. Regarding e-bike use, all age bands have witnessed growth. People over 60 years old have the highest share and highest growth rate of e-bike use. This is different from our expectation that younger people are increasingly using more e-bikes for work commute, which will be further elaborated in Section 4.3. *E*-bike use has the highest share for commutes of less than 10 km, showing steady growth over the years. The 10–15 km commute distance category has also experienced an increase in e-bike use. Regarding the degree of urbanity at the home location, the share of e-bike trips originating from very highly urban areas is relatively lower than the other degrees of urbanity. Furthermore, there is a substantial rise in e-bike trips generated in non-urban areas.

4.2. E-bike ownership models

Table 7 shows the results of the binary logistic models for e-bike ownership as a function of socio-demographic and built environment variables, as defined in Eqs. (5) and (7). The Table's last three columns indicate changes in coefficients across the time periods compared to the base period (2014–2015). Significant changes in these coefficients mean that the effect of a factor has changed compared to the base period.

Table 6
Characteristics of independent variables in the models over the periods.

	2014–15		2016–17		2018–19		2020–21	
	Mean or %	S.D.	Mean or %	S.D.	Mean or %	S.D.	Mean or %	S.D.
Socio-demographic								
Car ownership	85.6 %		84.5 %		81.9 %		85.6 %	
Household size 3+	33.6 %		32.2 %		30.7 %		32.6 %	
Income	61.5 %		65.3 %		62.1 %		62.2 %	
Household composition (ref: single family)								
Couple	26.0 %		25.9 %		26.6 %		26.0 %	
Couple with child(ren)	46.6 %		44.8 %		44.3 %		47.2 %	
Other	9.7 %		10.2 %		8.5 %		8.2 %	
Age (ref: 60+)								
Age 0–29	25.5 %		26.1 %		26.2 %		26.4 %	
Age 30–39	20.2 %		21.0 %		20.7 %		19.1 %	
Age 40–49	23.8 %		22.3 %		20.7 %		19.0 %	
Age 50–59	21.8 %		21.2 %		20.9 %		22.4 %	
Man (ref: woman)	56.0 %		56.2 %		55.5 %		55.5 %	
Education less than MBO or equivalent	40.6 %		41.4 %		41.1 %		41.2 %	
Full time employment	67.6 %		68.1 %		65.9 %		62.5 %	
Built environment								
Degree of urbanity (ref: very highly urban)								
Highly urban	29.4 %		29.7 %		30.0 %		30.3 %	
Moderately urban	18.6 %		17.1 %		15.5 %		15.4 %	
Low urban	20.9 %		20.6 %		19.6 %		22.8 %	
Non-urban	9.0 %		8.4 %		7.0 %		7.9 %	
Potential accessibility	2.0	2.2	2.2	2.7	2.4	2.4	2.0	2.1
Commute distance (>20 km)								
0-5 km	33.3 %		33.0 %		30.2 %		35.0 %	
5-10 km	17.6 %		17.4 %		15.6 %		17.2 %	
10-15 km	10.7 %		11.0 %		9.8 %		10.2 %	
15-20 km	8.0 %		8.1 %		7.8 %		7.8 %	

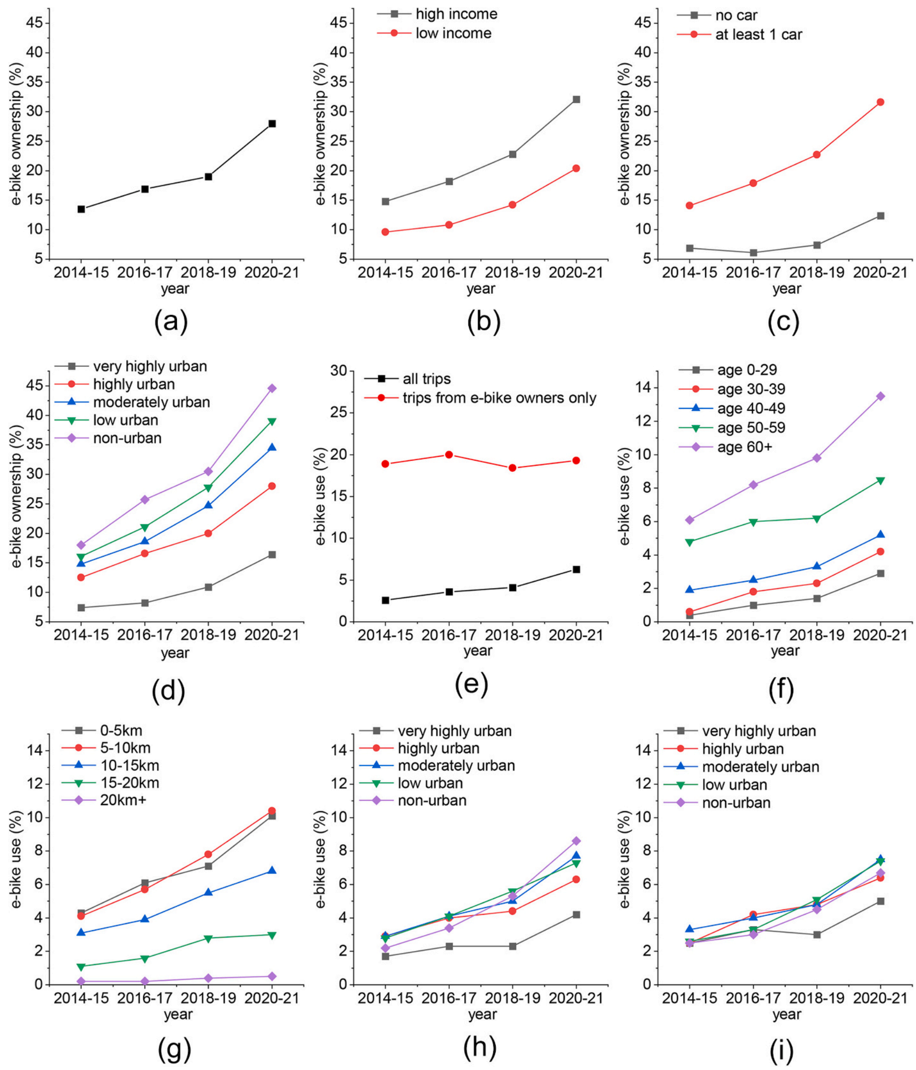

Fig. 5. Share of e-bike owner households from all households and share of e-bike trips from all trips per period.

In order to choose a subset of independent variables that best explains the variations in e-bike ownership, several steps were taken. First, in each variable group (i.e., socio-demographic and built environment variables), variables with high correlations with the dependent variables were identified. Second, multivariate models were estimated with different combinations of independent variables. The tested variables were based on expectation and/or their high correlation with the dependent variable. Here, variables were identified that: i) have a significant relationship with the independent variable in line with theory; ii) show a robust behavior in terms of sign and significance; iii) have low multi-collinearity with other variables in the variable group (The VIF (Variance Inflation Factor) values, measuring how much the variance of the estimated regression because of collinearity, are lower than 5 (Kutner et al., 2005; Rogerson, 2019)), and iv) contribute to a relatively higher model performance. Finally, the most robust variables in terms of sign and significance were chosen while taking into account theoretical expectations, multi-collinearity and overall model performance.

The pseudo R-squared values of the ownership models (models 1–4 and model 9) show the approximate percentage of variance accounted for by the models. The changes from one year to the next are small. In model 1, car ownership has a negative correlation with e-bike ownership. However, post-2016 analyses indicate that this relationship turns positive, as evidenced by the subsequent models (2 through 4). Model 9 further supports this change, indicating negative coefficients in the base period and positive change of coefficients for the interaction terms for the years 2016–2017, 2018–2019, and 2020–2021, indicating a positive and increasing trend in the association between car ownership and e-bike ownership compared to 2014–2015. This observation is also substantiated by the descriptive analysis, which reveals that the growth in e-bike ownership among households without cars over the years is not as pronounced as it is among those who own cars (Fig. 5.c).

Model 9 shows an increase in car ownership coefficient from the base period 2014–2015 with a value of -0.01, rising to 0.11 ($= -0.01 + 0.12$) in the 2016–2017 period, 0.40 ($= -0.01 + 0.41$) in 2018–2019, and reaching 0.45 ($= -0.01 + 0.46$) in 2020–2021. In contrast, the cross-sectional models (models 1–4) show an upward trend until 2018–2019 (model 3), followed by a slight decline in 2020–2021 (model 4). One possible reason for this difference is that cross-sectional models capture a snapshot of relationships at a specific point in time, while the pooled model tracks changes in the coefficients across multiple time points, relative to the baseline. The decline in 2020–2021 observed in the cross-sectional models corresponds with the car ownership increase in the sample (Table 6). Higher car ownership might reduce the perceived dependence on e-bikes for commuting, which explains the diminished influence of car ownership on e-bike ownership in the cross-sectional model. This immediate, period-specific influence is captured by the cross-sectional models but not by the pooled model, which reflects broader patterns and long-term changes. For investigating trends

Table 7
Binary logistic results for household e-bike ownership.

	Model 1		Model 2		Model 3		Model 4		Model 9 pooled (2014–21)							
	2014–15		2016–17		2018–19		2020–21		Base period		Changes in coefficients compared to 2014–15					
									2014–15		2016–17		2018–19		2020–21	
	B	S.E.	B	S.E.	B	S.E.	B	S.E.	B	S.E.	B	S.E.	**B**	S.E.	B	S.E.
Car ownership	−0.04***	0.01	0.38***	0.01	0.40***	0.00	0.28***	0.01	−0.01***	0.01	0.12***	**0.01**	0.41***	0.01	0.46***	0.01
Household size 3+	−0.27***	0.01	−0.27***	0.01	−0.09***	0.00	−0.13***	0.00	−0.27***	0.01	0.00	0.01	0.12***	0.01	0.14***	0.01
Income	−0.24***	0.00	−0.10***	0.00	−0.11***	0.00	−0.09***	0.00	−0.23***	0.00	0.02***	0.01	0.12***	0.01	0.22***	0.01
Household composition (ref: single family)																
Couple	0.92***	0.01	1.03***	0.00	0.92***	0.00	0.94***	0.00	0.93***	0.01	0.01	0.01	−0.01**	0.01	0.09***	0.01
Couple with child(ren)	0.68***	0.01	0.89***	0.01	0.69***	0.01	0.90***	0.01	0.69***	0.01	0.12***	0.01	0.00	0.01	0.29***	0.01
Other	0.38***	0.01	0.12***	0.01	0.44***	0.01	0.36***	0.01	0.39***	0.01	−0.37***	0.01	0.05***	0.01	0.04***	0.01
Degree of urbanity (ref: very highly urban)																
Highly urban	0.06***	0.01	0.50***	0.01	0.25***	0.01	0.17***	0.01	0.09***	0.01	0.17***	0.01	0.15***	0.01	0.31***	0.01
Moderately urban	0.13***	0.01	0.48***	0.01	0.35***	0.01	0.35***	0.01	0.17***	0.01	0.06***	0.01	0.18***	0.01	0.45***	0.01
Low urban	0.20***	0.01	0.63***	0.01	0.49***	0.01	0.45***	0.01	0.23***	0.01	0.13***	0.01	0.25***	0.01	0.51***	0.01
Non-urban	0.28***	0.01	0.89***	0.01	0.56***	0.01	0.57***	0.01	0.32***	0.01	0.28***	0.01	0.29***	0.01	0.57***	0.01
Potential accessibility	−0.18***	0.00	−0.11***	0.00	−0.17***	0.00	−0.19***	0.00	−0.18***	0.00	0.01***	0.00	0.01***	0.00	0.06***	0.00
LR Chi^2 (*P*-value)	238,414(0.00)		233,001(0.00)		250,605(0.00)		240,867(0.00)		1,050,474(0.00)							
R-squared	0.10		0.11		0.13		0.11		0.13							

NOTE: Significance levels: * $p < 0.10$; ** $p < 0.05$, *** $p < 0.01$.
The changes in coefficients indicate the coefficients of the interaction terms with each time point. They are the effects of the independent variable at that time point compared to the base time point, i.e. 2014–15. The sums of coefficients for the main and interaction effects for each time can be interpreted as the ‘period-specific’ coefficient.

and drawing conclusions about long-term trends in the various socio-demographic and built environment factors, only the pooled models will be used in subsequent analyses.

As shown in models 1 to 4, household size more than 3 has a significant negative relation with e-bike ownership. Model 9 lends partial support to this and shows a decrease trend in this negative association (Fig. 6). By adding the changes in coefficients, the negative impact for the periods 2018–2019 and 2020–2021 is mitigated from −0.27 to −0.15 (= −0.27 + 0.12), and from −0.27 to −0.13 (= −0.27 + 0.14), respectively. This trend suggests a decreasing impact of household size on the propensity to own e-bikes.

Models 1–4 indicate that households with relatively higher incomes are more inclined to possess e-bikes. This might be caused by the fairly high price of the e-bike in the market, ranging from 800 to 6000 euros with different options (ING, 2021). The magnitude of this association appears to decrease over time which is supported by model 9: Income's impact for 2016–2017, 2018–2019 and 2020–2021 are mitigated from −0.23 to −0.21 (= −0.23 + 0.02), from −0.23 to −0.10 (= −0.23 + 0.12), and from −0.23 to −0.01 (= −0.23 + 0.22), respectively (Fig. 6). This decreasing effect might be caused by lower-income households increasingly owning e-bikes (Fig. 5.b). These model results support Hypothesis (1), which posits that the strength of the relationship between socio-demographic factors and e-bike ownership changes over time. Compared to single-person households, couples, couples with child (ren) or other household compositions are more likely to own an e-bike.

Compared to very highly urban areas, the likelihood of e-bike ownership is higher in less urbanized areas. The observation could be attributed to the fact that densely populated areas offer greater ease of access to various destinations through walking or cycling and usually benefit from better transit coverage. Additionally, in relatively more urbanized areas, circulation is constrained and interrupted by the constant presence of intersections and traffic signals. Therefore, the speed advantage of e-bikes is not fully realized, unlike in non-urban areas. Furthermore, the coefficients of moderately urban, low urban and non-urban areas witness a significant increase trend from the 2014–2015 period to the 2020–2021 period. The most significant change is observed for non-urban at the home location (Fig. 6). The potential accessibility at the home location has a negative correlation with e-bike ownership. This is probably because areas with high accessibility foster a diverse range of activities and reduced distances to and between activities, encouraging walking and cycling as viable transportation options. The effect of the potential accessibility decreases over time. These findings align with Hypothesis (2), which suggests that the relationship between the built environment and e-bike ownership changes over time. The distance to amenities variables were found to be not statistically significant, therefore not included in the model.

As a robustness check, sensitivity analyses are conducted by incorporating the private bike ownership and shared bike service availability into the models. The private bike ownership is collected by asking the respondent whether there is at least one conventional bike in the household in the OViN dataset. It is only available for the years 2014 to 2017. To assess its impact, the variable is included in Models 1 and 2. The results show no significant differences compared to the original models, with no changes in the direction of effects or the significance of variables. Regarding the shared bike service availability data, it is available for 2025 (Overpass-turbo, 2025). It represents if there's a shared bike at the PC4 level of the residential home location. Since the year closest to 2025 is 2020–2021, Model 4, which analyzes the period 2020–2021, was incorporated with the shared bike service data. The findings indicate that including the private bike ownership and shared bike service variables does not alter the conclusions drawn from the original models. Due to the unavailability of private bike ownership data for the period 2018–2021 and shared bike service data for the entire study period, and to ensure consistency across the entire analysis period, these variables were not included in the final models presented in the main manuscript.

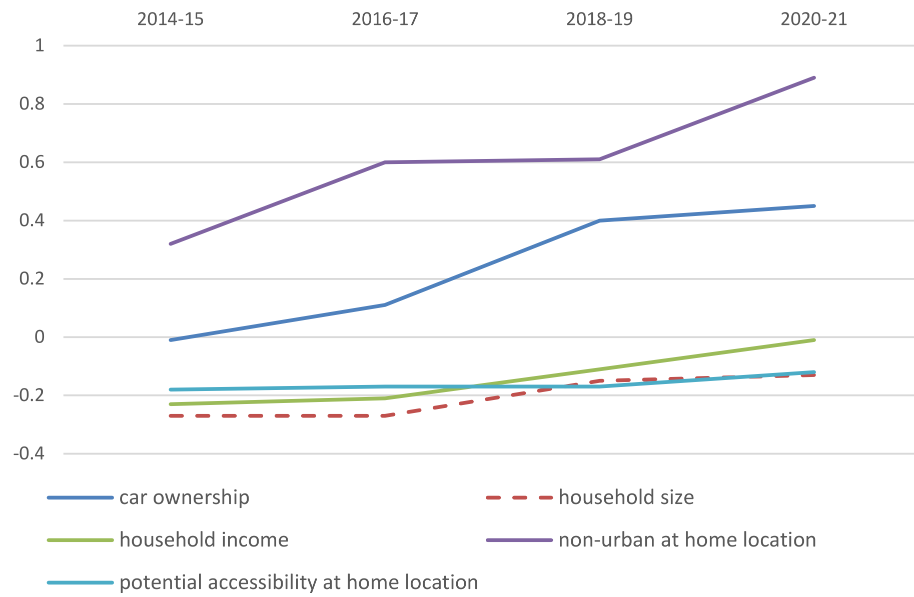

Fig. 6. Trends in coefficient from pooled model for e-bike ownership.

4.3. E-bike use models

Table 8 shows the results of the e-bike use models as defined in Eqs. (6) and (8). Similar steps to the ownership model were taken to choose a subset of independent variables that best explain variations in e-bike use.

As shown in models 5–8, people more than 60 years old are more inclined to commute with their e-bikes. In the analysis, trips from the 0–29 and 60+ age groups are only included if they are identified as work commute trips. Model 10 indicates that the changes in the coefficient for people younger than 40 years old are significant and positive, which is the most significant change in the model (Fig. 7). The consistent positive changes in the coefficients suggest that the difference between this age band and the 60+ age band is reduced, which means that though less than older adults, e-bike use is increasing among young people. The model results support Hypothesis (1) that the relation between age and e-bike use decreases over time. Possible reasons are: 1) the age group below 40 is becoming more open to adopting e-bikes being an innovative form of transport aligned well with their interests; 2) the pandemic has shifted the modal split away from public transport, as evidenced in our dataset, possibly due to social distancing, and e-bikes fit the need of the younger age band as a replacement; 3) the increasing popularity of e-bikes reinforced by peer influence and social media can contribute to the increased use of e-bikes among the youth. The model results show that women are more likely to use e-bikes for work commuting. This might be because, with an e-bike, people can reach greater distances in less time and with less effort, which empowers women to ride (KILDEN, 2015; Latz, 2021; Van Cauwenberg et al., 2019; Wild et al., 2021). As shown in model 10, over time, the magnitude of the effect of gender and education appears to become smaller (Fig. 7). This finding partially aligns with Hypothesis (2), which suggests that the relationship between gender and e-bike use decreases over time. The diminishing effects of gender and education on e-bike use indicate that e-bikes are increasingly used across broader demographics over time.

Similar to the ownership model, the share of non-urban areas in e-bike commutes is also rising over time (Fig. 7). In other words, the contribution of rural areas to e-bike ownership and e-bike trips for work is increasing (also observable from the steep rise in the descriptive Fig. 5.d and Fig. 5.h). The growing penetration of e-bikes in these areas can be due to several reasons: 1) the presence of high quality cycling infrastructure, such as cycling highways in the vicinity of these areas makes e-bike commuting more convenient and encourages more people to adopt and use e-bikes; 2) the open space and scenic landscapes in rural areas enhance the pleasure of cycling, making e-bikes a more attractive travel option; 3) increasing awareness of the health benefit of cycling and the environmental advantages of reducing car usage might motivate people to adopt and use e-bikes as part of a healthier and more sustainable lifestyle.

Interestingly, the correlation between potential accessibility at home location and e-bike ownership is negative and decreasing over time (Fig. 6). Similarly, the correlation between potential accessibility at work location and e-bike use follows the same trend (Fig. 7). The possible reasons are: 1) as e-bikes become more popular and affordable, their ownership and use might spread more evenly across all areas, regardless of accessibility, reducing the influence of accessibility on e-bike ownership and use over time and leading to a decline in the magnitude of the negative effect; 2) the weakening negative impact on e-bike ownership and use could result from a saturation effect of potential accessibility, reflecting a diminishing sensitivity to changes in accessibility over time (Goodwin, 2013).

The results of models 5 through 8 suggest that, from 2014 to 2021, individuals commuting less than 5 km exhibit a higher propensity for e-bike usage, followed by those commuting distances of 5–10 km. This finding differs slightly from the descriptive analysis, which indicates that in the period of 2018–2019 and 2020–2021, those commuting between 5 and 10 km are most likely to use e-bikes. This difference can be caused by the controlling of other factors in the regression analysis.

Similar to the e-bike ownership models, a sensitivity analysis was conducted to examine the robustness of the model results by incorporating the shared bike service variables into the models. The results showed no significant differences compared to the original models, indicating that the inclusion of the shared bike service variable does not alter the conclusions drawn from the original models.

5. Discussion

5.1. Role of socio-demographic and the built environment factors

Several findings about the role of various factors in e-bike ownership and use from this study are consistent with existing literature. Household size is found to be negatively correlated with e-bike ownership, which aligns with the results of Kroesen (2017) in a similar study conducted in the Netherlands. Additionally, older adults are more likely to use their e-bikes for commuting. Similar findings are found by de Kruijf

Table 8
model results for e-bike use.

	Model 5		Model 6		Model 7		Model 8		Model 10 pooled (2014–21)							
	2014–15		2016–17		2018–19		2020–21		Base period		Changes in coefficients compared to 2014–15					
									2014–15		2016–17		2018–19		2020–21	
	B	SE	B	SE	B	SE	B	SE	B	SE	B	SE	B	SE	B	SE
Socio-demographic																
Age (ref: 60+)																
Age 0–29	−2.71***	0.00	−2.33***	0.00	−1.77***	0.00	−1.46***	0.00	−2.65***	0.00	0.26***	0.00	0.68***	0.00	1.45***	0.00
Age 30–39	−2.09***	0.00	−1.27***	0.00	−1.19***	0.00	−0.88***	0.00	−1.93***	0.00	0.85***	0.00	0.92***	0.00	1.20***	0.00
Age 40–49	−1.03***	0.00	−1.01***	0.00	−0.98***	0.00	−0.84***	0.00	−1.08***	0.00	0.08***	0.00	−0.13***	0.00	0.45***	0.00
Age 50–59	−0.17***	0.00	−0.19***	0.00	−0.32***	0.00	−0.35***	0.00	−0.18***	0.00	0.03***	0.00	−0.27***	0.00	−0.08***	0.00
Male (ref: female)	−0.67***	0.00	−0.53***	0.00	−0.43***	0.00	−0.31***	0.00	−0.53***	0.00	0.01***	0.00	0.14***	0.00	0.27***	0.00
Education less than MBO or equivalent	−0.36***	0.00	−0.23***	0.00	−0.24***	0.00	−0.27***	0.00	−0.38***	0.00	0.06***	0.00	0.19***	0.00	0.22***	0.00
Full time employment	−0.06***	0.00	−0.31***	0.00	−0.18***	0.00	−0.18***	0.00	−0.08***	0.00	−0.31***	0.00	−0.07***	0.00	−0.18***	0.00
Built environment at home location																
Degree of urbanity (ref: very highly urban)																
Highly urban	0.24***	0.00	0.41***	0.00	0.25***	0.00	−0.03***	0.00	0.14***	0.00	0.18***	0.00	0.02***	0.00	−0.17***	0.00
Moderately urban	0.22***	0.00	0.31***	0.00	0.31***	0.00	0.08***	0.00	−0.13***	0.00	−0.05***	0.00	0.39***	0.00	0.25***	0.00
Low urban	−0.03***	0.00	0.54***	0.00	0.24***	0.00	−0.04***	0.00	0.02***	0.00	0.19***	0.00	0.27***	0.00	−0.05***	0.00
Non-urban	−0.06***	0.00	0.43***	0.00	0.20***	0.00	0.16***	0.00	−0.38***	0.00	0.26***	0.00	0.33***	0.00	0.62***	0.00
Potential accessibility	−0.14***	0.00	−0.07***	0.00	−0.13***	0.00	−0.14***	0.00	−0.08***	0.00	0.01***	0.00	−0.10***	0.00	−0.06***	0.00
Built environment at work location																
Degree of urbanity (ref: very highly urban)																
Highly urban	−0.44***	0.00	−0.01***	0.00	0.03***	0.00	0.01***	0.00	−0.43***	0.00	0.22***	0.00	0.59***	0.00	0.41***	0.00
Moderately urban	−0.05***	0.00	−0.09***	0.00	−0.02***	0.00	0.05***	0.00	−0.11***	0.00	−0.23***	0.00	−0.10***	0.00	0.10***	0.00
Low urban	−0.33***	0.00	−0.31***	0.00	−0.15***	0.00	−0.04***	0.00	−0.48***	0.00	−0.20***	0.00	0.22***	0.00	0.48***	0.00
Non-urban	−0.31***	0.00	−0.31***	0.00	−0.17***	0.00	−0.11***	0.00	−0.29***	0.00	−0.23***	0.00	0.01***	0.00	0.19***	0.00
Potential accessibility	−0.10***	0.00	0.00***	0.00	−0.07***	0.00	−0.02***	0.00	−0.12***	0.00	0.05***	0.00	0.05***	0.00	0.11***	0.00
Commute distance (>20 km)																
0-5 km	1.14***	0.00	1.28***	0.00	1.21***	0.00	1.27***	0.00	1.11***	0.00	0.22***	0.00	0.16***	0.00	0.23***	0.00
5-10 km	0.89***	0.00	0.91***	0.00	1.07***	0.00	1.10***	0.00	0.78***	0.00	0.06***	0.00	0.38***	0.00	0.26***	0.00
10-15 km	0.70***	0.00	0.77***	0.00	0.76***	0.00	0.70***	0.00	0.83***	0.00	−0.12***	0.00	−0.05***	0.00	−0.05***	0.00
15-20 km	0.20***	0.00	−0.16***	0.00	0.35***	0.00	−0.02***	0.00	0.25***	0.00	−0.15***	0.00	0.05***	0.00	−0.15***	0.00
LR Chi^2 (*P*-value)	345,201(0.00)		334,143(0.00)		374,694(0.00)		384,385(0.00)		657,512(0.00)							
R-squared	0.12		0.13		0.15		0.15		0.16							

NOTE: Significance levels: * $p < 0.10$; ** $p < 0.05$, *** $p < 0.01$.
The changes in coefficients indicate the coefficients of the interaction terms with each time point. They are the effects of the independent variable at that time point compared to the base time point, i.e. 2014–15. The sums of coefficients for the main and interaction effects for each time can be interpreted as the 'period-specific' coefficients.

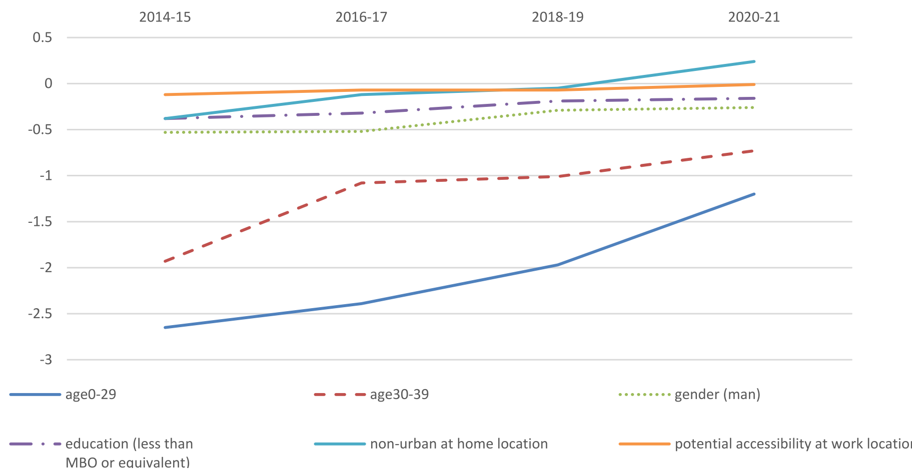

Fig. 7. Trends in coefficient from the pooled model for e-bike use (Note: potential accessibility at work location in the period of 2018–2019 is not significant).

et al. (2018) and de Kruijf et al. (2021).

The results show that e-bike ownership is positively related to household income and negatively related to the residential density of the home location. These findings align with Kroesen (2017) who also observes that increased e-bike ownership is associated with higher household income and lower residential density in the Netherlands. Similarly, Kohlrautz and Kuhnimhof (2024) find that higher household economic status and residence in less urban areas are linked to higher e-bike ownership in Germany despite differences in cycling culture, infrastructure, and geographical conditions compared to the Netherlands. In addition, consistent with the findings of this research, previous works from the Netherlands and the United Kingdom also find that women are more likely to use e-bikes. The studies above conducted in various countries find similar results, which align with the findings of this study. To better understand the broader applicability of these relationships, further research across diverse geographical contexts is recommended.

Some findings of this study differ from those in the previous literature. This research finds that individuals commuting 0–10 km are more likely to use e-bikes for their commutes than those traveling longer distances. This result aligns with the findings of de Kruijf et al. (2018) and Plazier et al. (2023). However, de Kruijf et al. (2021) report a contrasting trend, indicating that cycling distances above 5 km positively influence e-bike use for commuting. One possible explanation for this difference is that weather effects were controlled for in the analysis from de Kruijf et al. (2021), whereas this factor was not considered in this study. In addition, B. Sun et al. (2017) find that the built environment characteristics of the residential location are more influential on commute mode choice than the built environment at work locations. However, this distinction is not clearly evident in this study.

5.2. Shifting role of e-bike determinants

In this study, a diminishing influence of the 0–39 age group and gender on e-bike use is observed over the study period, which supports Hypothesis (1) that the role of socio-demographic factors changes over time. Similar findings from Huang et al. (2024) show that young people are increasingly choosing e-bikes and employing them more for work-related commutes in the Netherlands. They also find that in the Netherlands, e-bikes are more popular among women and this gap is gradually closing. Additionally, Plazier et al. (2023) find that e-bikes are widespread in rural areas and have potential for growth in the future based on a study from the northern part of the Netherlands. This trend is also observed in this study supporting Hypothesis (2) that the role of built environment factor in e-bike ownership and use changes over time.

Existing studies present mixed results on the role of car ownership. This study finds that in the period of 2014–2015, car ownership has a negative relationship with e-bike ownership, which shifted to a positive relationship after 2016. Kroesen (2017), using the same dataset from 2013 to 2015 in the Netherlands, finds no strong relationship between car and e-bike ownership. Although a significant negative correlation is identified in this study for the period of 2014–2015, the effect sizes are relatively small: −0.04 in the cross-sectional model and − 0.01 in the pooled model. Melia and Bartle (2021) observe that individuals who mostly or always commute by e-bikes are more likely to live in car-free households based on a survey conducted in the United Kingdom in 2019. However, this study specifically examines e-bike use for commuting, rather than e-bike ownership. In line with the findings from this study that car ownership positively correlates with e-bike ownership since 2016, Plazier et al. (2023) found a similar positive relationship based on a 2017 survey in the Netherlands. These findings suggest that the relationship between car ownership and e-bike ownership/use is context-dependent and evolves over time. Initially, car ownership appears to have a negative or weak correlation with e-bike use/ownership, possibly reflecting an earlier view of e-bikes as an alternative to cars. However, over time, the relationship has shifted to become more positive, suggesting that e-bikes are increasingly viewed as complementary to car ownership. The combination of car and e-bike ownership offers households greater flexibility and the ability to choose different transport modes based on convenience or need. Moreover, due to their relatively high cost, e-bikes are more likely to be owned by higher-income households, where multi-mode ownership and the flexibility it provides are financially viable, supporting a lifestyle with independent mobility choices. This evolution in behavior may be influenced by changing perceptions of e-bikes, improvements in infrastructure or shifts in urban mobility policies. Further research is needed to explore the underlying reasons for this change and to assess how these patterns differ across regions and over time. Policymakers aiming to promote e-bike use should consider the most recent data and account for geographical and cultural differences.

Furthermore, the share of e-bike owner households and e-bike commute trips in the Netherlands have witnessed an accelerated growth between the 2018–2019 period and the 2020–2021 period related to the e-bike growth in the COVID period, which is also found by Huang et al. (2024). The effect of potential accessibility at the home location also increased faster in this period compared to the earlier periods. However, to determine whether this trend is related to the pandemic or simply a sudden surge in e-bike popularity or behavior change in e-bike users, further studies incorporating post-2021 data are needed.

6. Conclusion, limitations and future direction

Using eight years of travel data from the Dutch national mobility surveys (2014–2021), this study examines the trends in e-bike ownership and e-bike use for work commute in the Netherlands. Furthermore, it uses cross-sectional and time series analyses to investigate the relationships between various socio-demographic and built environment determinants and e-bike ownership and e-bike use, and the evolution of these relationships across the study period.

The findings show that both e-bike ownership and e-bike use in the Netherlands have experienced consistent growth over time with an acceleration during the 2020–2021 period. Socio-demographic factors including car ownership, household income, household size, and household composition have significant relations with the likelihood of e-bike ownership. Additionally, older adults, women, and people with higher education are more likely to commute by e-bikes. Interestingly, a decreasing impact of household size and household income on e-bike ownership, as well as a diminishing influence of age group, gender and education on e-bike use are observed over the study period. These decreasing effects suggest that e-bikes are becoming more widely adopted across diverse socio-demographic groups, indicating a trend towards broader and more inclusive use. In other words, the traditional boundaries among e-bike user groups are becoming less distinct. Furthermore, our findings confirm that significant relationships exist between the built environment and e-bike ownership / e-bike use for work commute. First, people living in very highly urban areas are less likely to own e-bikes at home. Second, the contribution of non-urban areas to e-bike ownership and e-bike trips for work has increased over time. Third, individuals with commutes of up to 10 km are more likely to use their e-bikes for commuting to work compared to those with commutes exceeding 10 km.

Our findings are relevant for urban and transport planners, designers, researchers, policy makers and public authorities in understanding e-bike use and introducing effective design and policy recommendations to support it. They have several policy implications. First, the rise in e-bike ownership and its use for work commute necessitates an increase in the quantity and quality of facilities for e-bike storage and charging at home and work locations. Second, e-bikes are less and less associated with the older age group, higher educated, well-off and larger households. Furthermore, gender differences in e-bike use are decreasing. These socio-demographic shifts indicate that, instead of being seen as a niche travel mode, the e-bike should be recognized as a viable mobility option that is increasingly adopted. Third, e-bikes are increasingly being owned and used in rural areas and their ownership is lowest in very dense areas. This indicates that promoting the use of e-bikes instead of private cars could be most feasible and beneficial for residential locations with lower population density. Especially, e-bikes have a high-potential for adoption in rural mobility.

All in all, the emphasis of the recent Dutch mobility policy in stimulating e-bikes for (short) work trips is in line with the observed trends. This can be further enhanced by providing employees with (lease) e-bikes instead of lease company cars, and e-bikes facilities such as sheltered bicycle parking and charging opportunities at job centers. A careful study of the commute patterns of workers from low density residential areas in relation to job centers can help determine the optimal cycling routes to service the working population. Especially workers in low density settlements within a 0-10 km radius of work centers can be effectively connected through these routes. Here, e-bikes can be further promoted by introducing high quality bike-friendly infrastructures, such as cycling highways.

It is important to note the caveats of this study and the avenues for future research. First, the unexplained variation in our models could be due to certain missing influential factors such as transportation costs, the availability of e-bike parking/charging facilities at the work location, the availability of company cars and weather. Furthermore, the role of "subjective" determinants of e-bike travel demand that include lifestyle elements such as personal attitudes, new technology perception and location preferences need to be investigated as they are increasingly becoming important in developed countries (Deng and Zhao, 2022). In addition, while sensitivity analyses were conducted using the available private bike ownership data, future research should aim to incorporate more recent data on private bike ownership to better capture its role in shaping e-bike adoption and usage patterns throughout the full study period. Second, the mediating effect of e-bike ownership in the relationship between the built environment and commute mode choice needs further analysis. Structurally combining the ownership model and mode choice model could show both the direct and indirect contributions of the built environment to travel mode choice. Third, this research focuses on the use of e-bikes for the purpose of work commuting. *E*-bikes are also being used for other purposes such as shopping and especially leisure (Fishman and Cherry, 2016). There is a need to investigate the (changing) determinants of e-bike use for these travel purposes as well to gain a comprehensive understanding of its ownership and use trends. Fourth, built environment data, including the degree of urbanity and distance to amenities, at 4-digit postcode level is used in this study. Future research could incorporate a broader range of built environment indicators, such as distance to transit and public transport accessibility, analyzed at more detailed spatial units, such as the 6-digit postcode level. Additionally, spatial heterogeneity and possible transport modal substitutions could be examined to explore the extent of local variations in national patterns of e-bike usage. Furthermore, while this study includes an analysis of the potential influence of shared bike services on e-bike ownership and use, it does not extend to other forms of shared micro-mobility services, such as shared e-bikes and shared e-scooters. Future research could incorporate these additional forms of shared micro-mobility to provide a more comprehensive understanding of their influence on e-bike ownership and use. Fifth, this study applies a time series analysis to multiple cross-sectional datasets to investigate Dutch e-bike ownership and use trends. While it benefits from large numbers of observations and a nationwide coverage over several years, it is not a longitudinal panel investigation. Creating a pseudo-panel model or analyzing panel datasets can further clarify the long-term mechanisms in socio-demographic and built environment determinants and e-bike ownership and use at the individual level. Sixth, the COVID-19 pandemic introduces unique circumstances that likely influence the e-bike travel behavior. Future research could investigate the temporary and long-term behavior change in response to the pandemic. Finally, while our study investigates the trends in e-bike ownership and use and their determinants, some of our findings are specific to the Netherlands with its unique geography and cycling culture background and the period of analysis. There is a need for more empirical analyses of e-bike ownership and use trends and their determinants across a variety of time periods and regions with different geographical, cultural and policy backgrounds to shed light on the various local and context-specific mechanisms at work.

CRediT authorship contribution statement

Yushan Zhang: Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Dena Kasraian:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Investigation. **Pieter van Wesemael:** Writing – review & editing, Supervision.

Data availability

The authors do not have permission to share data.

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