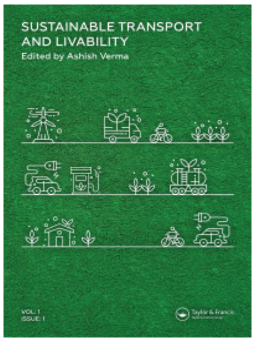

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E-bike ownership and usage: an analysis of Germany

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ABSTRACT
E-bikes have the potential to promote sustainable mobility by increasing the mode share of cycling. This paper examines their impact on travel behavior in Germany, taking into account socio-demographic groups and attributes, using the 2017 German national travel survey MiD. Two logit models investigate the factors influencing the ownership of different types of bicycles and the influence of bicycle type on mode choice. During the data collection period of 2016/2017, e-bikes were less common than conventional bicycles and were predominantly owned by older age groups. The models indicate that higher household economic status is associated with increased e-bike ownership, while urban residents have lower e-bike ownership and usage rates. E-bike owners cycle longer distances per day and have an increased cycling range because their cycling share is less affected by distance. However, e-bikes do not appear to substitute car ownership, and their use depends more on the season compared to conventional bicycles. Our results support findings from other countries, indicating partial cross-national transferability. Conflicting findings, such as e-bikes increasing cycling among young owners to a lesser extent and advanced age not reducing e-bike use, indicate a need to examine how national framework conditions influence the adoption and use of e-bikes.

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KEYWORDS E-bike; cycling; mode choice; household travel survey; travel behavior

1. Introduction

The diffusion of e-bikes is expected to promote sustainable mobility by encouraging cycling (Schleinitz et al., 2016; Sun et al., 2020). Previous research has shown that e-bikes are used for longer trips because of their higher speed and

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lower physical effort required compared to conventional bicycles (Plazier et al., 2017). Therefore, they have the potential to enhance overall health, reduce car traffic and associated emissions, and decrease space consumption and traffic-related accidents (Castro et al., 2019; Kroesen, 2017). The rise in e-bike sales, particularly in Western Europe, suggests that they could help achieve emission targets. Furthermore, e-bikes are anticipated to facilitate the use of active mobility even for individuals with medical conditions or low fitness levels, as well as enable older age groups to cycle despite declining physical abilities (MacArthur et al., 2018). From an equity perspective, however, the high cost of e-bikes compared to conventional bicycles raises concerns about their affordability for low-income groups. Although there have been several previous studies, Bourne et al. (2020) identified a research gap in the impact of e-bike ownership on travel behavior, particularly in relation to age, gender, and socioeconomic status. Our paper analyzes the influence of these variables and identifies the benefits of e-bikes and their advantages over conventional bicycles in terms of transportation planning.

For this analysis, we use data from Germany. We chose this country due to its early adoption of e-bikes and the lack of research on the resulting impact on mobility behavior. The data represents an intermediate step in the development of the e-bike market. The results are relevant for other countries with conditions similar to Germany, these being mixed topography, climate, and moderate cycling infrastructure quality, that are experiencing a rise in e-bike ownership and usage rates. The study excludes any potential effects of the pandemic, as the data collection period occurred before the COVID-19 outbreak.

This paper presents two logit models based on the German national travel survey MiD from 2016/2017 (Nobis & Kuhnimhof, 2019). The first model focuses on the ownership of different bicycle types, recognizing that e-bike owners may not be a representative sample of the population. The second model analyzes the impact of e-bike ownership versus conventional bicycle ownership on mode choice at the trip chain level, taking into account length, purpose, season, and age to determine how e-bike ownership influences the mobility behavior of its owners.

This paper defines "e-bike" as pedelecs according to European regulations. In contrast, "c-bike" refers to conventional bicycles without motor power assistance. Cycling as a mode of transportation includes riding both c-bikes and e-bikes.

The paper aims to investigate the factors that influence the ownership and usage of conventional and e-bikes. The analysis collects indicators to examine whether e-bikes encourage sustainable mobility by affecting mode choice. In the discussion, we compare our findings with those of other countries to determine whether e-bike ownership and usage in Germany are similar to that of other countries.

First, we will review previous research and describe our data and methods used. Next, we will present our results. Finally, we will discuss them and draw conclusions.

2. Literature review

This section begins with an overview of e-bike regulation and the role of e-bikes in Germany at the time of data collection. Following this, we provide a summary of previous research on e-bike ownership and use.

2.1. Regulation and the rise of e-bikes in Germany

In Germany, most e-bikes are classified as pedelecs and thus considered bicycles. However, internationally, there are various types of e-bikes and corresponding legal regulations (MacArthur & Kobel, 2017). E-bikes can be classified as bicycle-style or motorbike-style vehicles. In China, most e-bikes belong to the latter category (Fishman & Cherry, 2016). In countries such as the USA and Australia, bicycles are required to have operable pedals to be classified as such. In many countries, motor assistance is permitted only when pedaling, as is the case in the EU (Rose, 2012). Table 1 displays the German classification of e-bikes, with "pedelecs" referring to standard pedelecs and "s-pedelecs" referring to speed pedelecs.

E-bike sales in Germany have grown rapidly in recent years. In 2012, only 0.4 million e-bikes were sold. By 2017, at the time of data collection, sales had already risen to 0.7 million. Annual sales continued to grow in the following years, reaching 2.2 million in 2022, making it one of the most important markets worldwide, after China. E-bike sales are projected to surpass those of conventional bicycles for the first time in 2023 (ZIV, 2023). Although e-bikes are becoming more popular, they were still considered a niche market at the time of data collection, and this remains true for markets in other countries.

2.2. Previous research on e-bike ownership and usage

In 2020, Bourne et al. (2020) published a comprehensive literature review on the effects of e-bikes on travel behavior. The review includes both experimental studies, where participants received e-bikes for a period of time, and

Table 1. Classification of e-bikes in Germany.

	Pedelec	S-Pedelec
Motor assistance up to [km/h]	25 while pedaling	45 while pedaling
Regulatory	Bicycle	Motorcycle
Requiring driver's license and license plate	No	Yes

non-experimental studies, often conducted through web-based surveys. Most of the studies in this area analyze e-bike use after the purchase of an e-bike. Overall, e-bike users cycle longer distances per trip compared to c-bike users.

Table 2 summarizes the relevant literature findings on the impact of e-bikes on travel behavior. An example of an experimental study conducted by Fyhri and Fearnley (2015) provided e-bikes to Norwegian Automobile Federation members for two or four weeks and recorded their trips along with the distance per trip. The study indicates an increase in cycling shares among the e-bike test users, regardless of age. Additionally, the weekly cycling activity for commuting increased more than for exercise, which is consistent with other literature findings (Kroesen, 2017). Fyhri and Sundfør (2020) also conducted a study on the effects of purchasing an e-bike. They found that after acquiring an e-bike, the daily cycling distance increased from 2.1 km to 9.2 km, and the share of cycling as a mode of transportation increased from 17% to 49%.

Other studies have investigated the reasons for using e-bikes. MacArthur et al. (2018) conducted a web-based survey of e-bike owners and users in the USA. They found that the main reason for buying an e-bike was the intention to replace car trips. Other motivations included the comfort of motor-assisted cycling, particularly in hilly areas or for users with medical conditions, as well as fitness and recreation. The vast majority of the respondents had ridden a c-bike before owning an e-bike. The study discovered that purchasing an e-bike decreased the frequency of c-bike riding, but increased the total distance cycled. Additionally, e-bike users reported using it as their primary mode for a variety of trip types. Older individuals used them for recreational trips, while younger individuals used them for commuting. Respondents indicated that they would not have taken recreational trips if they did not own an e-bike. However, 46% of e-bike commuting trips replaced car trips.

Further research has focused on the impact of e-bikes on individual health and has found it to be positive (Castro et al., 2019; Lobben et al., 2019). However, it is important to note that e-bike owners are not representative of society due to the positive relationship between income and e-bike ownership (Fishman & Cherry, 2016; Kroesen, 2017; Popovich et al., 2014).

E-bikes have a low mode share in most Western countries. In China, however, e-bikes are the primary mode of transportation for commuting, particularly in cities with less than 500,000 inhabitants, due to the ban on gasoline motorcycles (Gu et al., 2021; Hu et al., 2021). E-bikes are primarily used as a substitute for public transportation in China. In contrast, in Europe, North America, and Australia, they are more commonly used to replace car trips (Bigazzi & Wong, 2020).

Studies investigating cycling and e-bike usage that rely on web-based surveys and self-recruitment strategies, as well as experimental studies that involve the temporary provision of e-bikes, may be affected by self-selection bias (Castro et al., 2019; Plazier et al., 2017). Therefore, the participants in these studies may

Table 2. Key findings of the influence of e-bikes on mobility behavior.

Citation	Location of study	Methods	Survey period	Key findings
Bigazzi and Wong (2020)	World-wide	Meta study	2006–2017	• E-bikes displace more transit trips in China and more car trips in Europe, North America, and Australia.
Castro et al. (2019)	Europe	Longitudinal survey, travel diaries, sampling strategy across cities	2014–2017	• The average cycling trip duration of e-bike owners (35.0 for a c-bike and 41.9 min for an e-bike) is significantly higher than that of c-bike owners (25.6 min). • Average trip distance is significantly different when comparing e-bike owners (9.4 km for e-bike trips and 8.4 km for c-bike trips) with c-bike owners (4.8 km for c-bike trips). • Average daily cycling time is similar for e-biking among e-bike owners and c-biking among c-bike owners (32.2 vs. 30.3 min), but e-bike owners also cycle 13.4 min on a c-bike. • E-bike owners travel significantly longer daily distances by e-bike than c-bike owners travel by c-bike (8.0 vs. 5.3 km per person per day). In addition, e-bike owners travel 2.5 km/d by c-bike. • E-bikers tend to substitute their primary mode of transportation.
Cherry et al. (2016)	CN	Travel diaries	2006–2012	• Many of those transitioning from non-motorized modes (ie walking and bicycle) to e-bikes would transition from e-bikes to more motorized modes (bus, taxi, car). 24% of e-bike trips would have been made by car (including taxis).
Fyhri and Sundfør (2020)	NOR	Travel diaries, panel	2014	• After purchasing an e-bike, the average distance traveled by bicycle increased from 2.1 to 9.2 km, and the mode share by bicycle increased from 17 to 49%. The increase in cycling km is slightly lower in the purchase case than in the experimental loan case, but the mode share is higher.
Fyhri and Fearnley (2015)	NOR	Travel diaries, experimental	2013	• Loaning an e-bike to users increases cycling, expressed in the number of trips, distance cycled, and cycling share. The effect is more remarkable for women than for men. The impact on distance cycled is the greatest for non-commuting trips.

(*Continued*)

Table 2. Continued.

Citation	Location of study	Methods	Survey period	Key findings
Kroesen (2017)	NL	1-day Travel diaries	2013–2015	• On average, e-bike owners travel 3.0 km with their e-bike, while non-e-bike owners travel 2.6 km with their c-bike. E-bike owners travel an additional 0.9 km/day by c-bike. • E-bike owners travel less by car (−5.8 km) and by public transportation (−9.4 km). They also travel less overall than non-e-bike owners. • E-bike ownership reduces c-bike ownership from 81 to 49% but correlates with slightly higher car ownership. Neither the ownership of an e-bike nor a c-bike acts as a car substitute. • In terms of mode use, e-bike ownership increases the use of e-bikes and decreases the use of c-bikes, car driving, and public transportation. • The signs of the effects of socio-demographic and household variables on e-bike use are opposite to the impact of these variables on e-bike ownership. For example, age increases the probability of owning an e-bike but has a negative effect on e-bike use.
MacArthur et al. (2018)	USA	Online survey	2017	• The main reasons for buying an e-bike are: to replace car trips, to ride with less effort, for recreation purposes, because someone lives or works in a hilly area, or to improve fitness. • Most e-bike users (93.4%) rode a c-bike before owning an e-bike. The e-bike leads to falling c-bike use but increases total cycling. • Exercise, recreation, and commuting are the trip purposes most likely to be made primarily by e-bikes. Older people and those with physical limitations are likelier to use e-bikes for recreational and exercise-based trips. In contrast, younger people and those without physical limitations use the e-bike as their primary mode of commuting. • E-bikes also replace many trips that people would have made by active or public transit modes, most of which are commuting (39.8%) and recreation or exercise trips (29.4%).

(*Continued*)

Table 2. Continued.

Citation	Location of study	Methods	Survey period	Key findings
Plazier et al. (2017)	NL	GPS-based travel diaries and in-depth interviews	2015–2016	• E-bike use is highest for work-related, single-destination trips. • Participants state that commuting by e-bike gives them the advantages of cycling over motorized transport (enjoyment of outdoor, physical activity; independence) while mitigating its relative disadvantages (longer travel time; increased effort). • Results demonstrate that e-bikes can substitute motorized commuting modes for distances perceived as too long to be covered by c-bike, and stress the importance of a positive experience in e-bike commuting.
Sun et al. (2020)	NL	Travel diaries, panel	2013–2016	• The results indicate that purchasing an e-bike reduces the use of a c-bike more significantly than driving a car or walking. Looking at the level of cycling by e-bike and c-bike together, the share of cycling almost doubles, while the car remains the main mode of transport despite a 16% drop in mode share. • C-bike ownership drops from 81.3% to 43% after purchasing an e-bike, while car ownership drops from 92.5 to 86.9%. • E-bikes boost cycling trips mostly for distances between 5 and 20 km, indicating a range extender effect for cycling. • For commuting, e-bike trips challenge the dominance of car trips, as the car mode share drops from 76.3% to 50.8%. • People living in highly urbanized areas are less likely to reduce their car use after adopting an e-bike than new e-bikers in non-urbanized areas.

not be representative of the general population, as those who participate have a strong identification with their bicycle-based mobility. Panel surveys are an alternative data source. These studies analyze the impact of purchasing an e-bike between survey periods rather than comparing individuals who own e-bikes to those who do not. However, due to the previously low penetration of e-bikes in developed countries, there are only a small number of actual e-bike buyers in these surveys. As a result, the resulting samples lead to insignificant results, particularly for the influence of socio-demographic factors (Fyhri & Sundfør, 2020; Sun et al., 2020).

Instead, national travel surveys provide data with sufficiently large subsamples of e-bike owners. For instance, Kroesen (2017) analyzed e-bike ownership, usage, and their effects on mobility behavior in the Dutch national travel survey. The author found, through descriptive analysis, that owning an e-bike strongly reduces the ownership of c-bikes. In addition, e-bike owners travel shorter distances per day on their c-bike (−1.7 km) and even shorter distances by car (−5.8 km) and public transport (−9.4 km) than non-owners. However, the study found no evidence suggesting that e-bike ownership is a substitute for car ownership. The study demonstrated that owning an e-bike leads to a substantial increase in e-bike use, a significant decrease in c-bike use, and a reduction in car and public transportation use, using a structural equation model (SEM). It also found a positive correlation between age and e-bike ownership and a negative correlation between age and e-bike use. However, Kroesen (2017) did not examine mode choice at the trip level, considering factors such as trip length and purpose.

Germany is an interesting region for investigating the impact of e-bikes because of their early adoption. Nevertheless, there are currently no scientific publications on e-bike usage in Germany, leaving their impact on mobility behavior in the country uncertain. This raises the question of whether findings obtained from the national travel survey in Germany would be consistent with those from other countries using different data and methodologies.

3. Data and methodology

First, we present information about the dataset. Next, we describe our data preparation and our modeling approach.

3.1. Dataset

This paper uses the B1 standard dataset from the German national household travel survey MiD from 2016 and 2017, which includes 316,361 individuals from 156,420 households who made a total of 960,619 trips (Nobis & Köhler, 2019). The travel survey contains information on e-bike ownership at the individual level and e-bike use at the trip level. For both the descriptive and the multivariate analyses in this paper, we used the weights provided in the original person and trip datasets. For more information on their calculation, we refer to Eggs et al. (2019). The dataset includes as an important variable the household's economic status, which is, in short, a five-level household classification according to equivalent income (net household income relative to household size). For details on the estimation of this variable, see Nobis and Köhler (2019).

3.2. Data preparation

For data preparation, we first removed observations with missing values from the dataset. For instance, we excluded individuals under the age of 16 from the sample used for model estimation, as they were not asked about e-bike ownership. Consequently, the sample size for estimating the individual-level bike ownership model was 184,061 people. In contrast to previous studies that distinguish between ownership of c-bikes and e-bikes, we differentiate between individuals who own (a) no bicycles, (b) c-bikes only, (c) e-bikes only, and (d) both c- and e-bikes.

At the trip level, we followed a similar procedure and excluded individuals with missing or unclear values. Furthermore, we estimated the total length, main purpose (order: work and education, purchase, private errands, leisure activities), and the main mode of transportation (order: public transport, car, cycling, walking) of the trip chains. This resulted in 268,492 trip chains suitable for model estimation. Since bike-sharing is not prevalent in Germany, we excluded individuals without a bicycle as cycling was not an option for them. We also excluded individuals who did not report permanent car ownership or did not possess a driver's license to focus solely on travelers with multiple options. Additionally, we restricted our analysis to trip chains that were no longer than 50 km. This resulted in a sample of 162,481 trip chains made by 99,734 individuals as input for the mode choice model. Furthermore, we combined the groups of e-bike and c-bike owners and e-bike owners only due to their relatively small numbers.

3.3. Modeling approach

This paper uses multinomial logistic regression, a technique commonly used in transportation planning, to estimate multivariate models. Thus, it allows running two logit models, one for factors explaining e-bike ownership at the individual level and another for the mode choice at the trip chain level to examine both who owns e-bikes and how the ownership influences mode choice. Multinomial logistic regression allows for the analysis of decisions between multiple discrete alternatives. The utility U_{qi} of an alternative i for an individual q is given by:

$$U_{qi} = V_{qi} + \varepsilon_{qi} \; \forall \mathrm{i} \tag{1}$$

The V_{qi} represents the objective utility, while the ε_{qi} is an unobservable component that follows a type I extreme value distribution, also called Gumbel distribution. Assuming that these terms are independently and identically distributed allows for relative comparisons between odds, making logit models useful for analyzing the influence of different independent variables, such as socio-demographic attributes and bicycle ownership, on dependent variables like mode choice. Finally, the probability of an alternative being chosen is given by:

$$P_{qi} = \frac{e^{V_{qi}}}{\sum_i e^{V_{qi}}} \tag{2}$$

For more information on the methodological background, please refer to McFadden (1974) and Profillidis and Botzoris (2019). All models were executed in R using the mlogit package.

For the bicycle ownership model, we also tried nested logit models but decided against using them because they delivered less good results.

We chose reference levels to deliver meaningful results and to avoid very restricted reference groups. For example, we selected a medium household income as the reference category in the first model and the combination of work and "other trip purposes" in the second model. This is because an extreme income or an uncommon trip purpose would lead to less meaningful reference categories.

We identified relevant independent variables through an iterative procedure by varying them and observing model parameters, such as McFadden pseudo-r^2. We excluded insignificant variables, such as joint variables of e-bike and car ownership, day-specific weather variables, or overly detailed combinations with spatial typologies. We use different sets of variables in the bicycle ownership model and in the mode choice model to account for the varying relevance and significance of variables depending on the object of observation. For example, the economic status of the household had a significant influence only on bicycle ownership. Therefore, only the bicycle ownership model considers the household's economic status.

4. Results

4.1. Descriptive analysis of c-bike and e-bike ownership

In 2017, e-bikes were less common than c-bikes in Germany, likely due to their higher purchase price and their then-recent emergence, resulting in a much smaller accumulated stock. Bicycle ownership is dependent on the economic status of the household, as shown in Figure 1. As wealth increases, there is a corresponding increase in the ownership of c-bikes and, particularly, e-bikes. Individuals from households with medium-level incomes have the highest percentage of only e-bike ownership, while individuals in wealthier households are more likely to own both an e-bike and a c-bike.

Figure 2 shows that e-bike ownership is primarily concentrated among middle-aged and older individuals. The absence of any type of bicycle increases rapidly from the age of 70 onwards, probably due to the declining physical ability to cycle.

Compared to owning a c-bike, owning an e-bike is associated with an increase in daily cycling distance, as shown in Table 3. Individuals who own both a c-bike

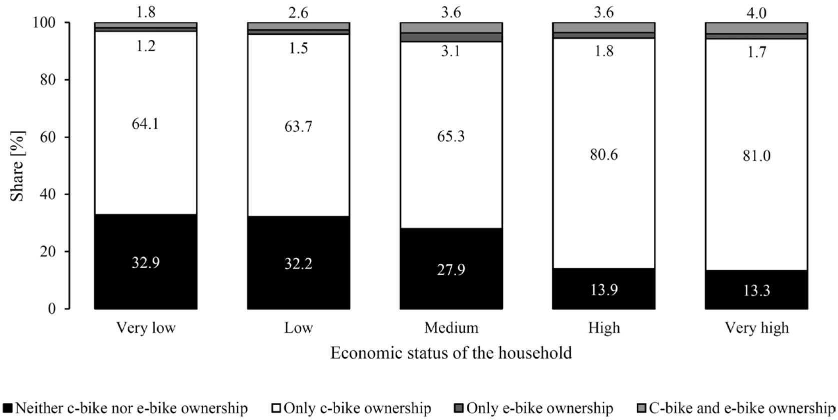

Figure 1. Bike ownership on the individual level by the economic status of the household ($n = 188,900$).

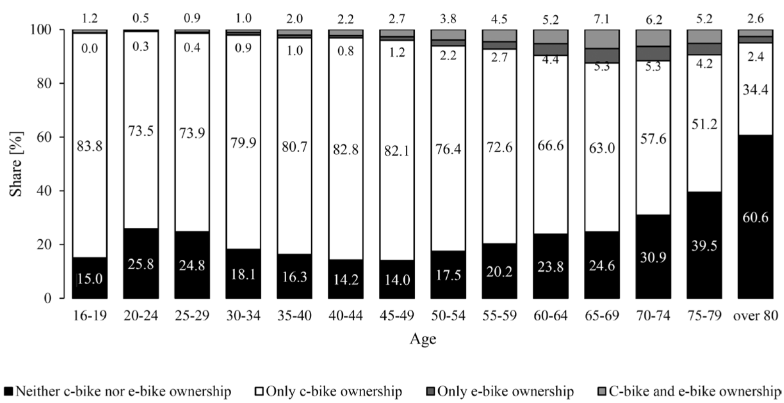

Figure 2. Bike ownership related to age ($n = 188,900$).

and an e-bike cycle more than twice the distance per day than those who own only a c-bike. There is no clear correlation between bicycle type and daily car mileage. Individuals who own a c-bike have the highest value, while those who do not own any bicycle have the lowest. This finding may be explained by correlations with other socio-demographic factors. For example, non-bicycle ownership is higher among immobile persons.

4.2. Multivariate analysis of c-bike and e-bike ownership

Table 4 presents the results of the logit model for bicycle ownership, with "no bike ownership" as the reference level. The intercept is positive only for c-bike ownership, while it is negative for c-bike and e-bike ownership and far below zero for only e-bike ownership. The coefficients reflect the fact that e-bikes are much less common than c-bikes, as positive values increase the probability, and negative values decrease it. The table shows that individuals from households with a below-average economic status have lower rates of bicycle ownership. As previously shown in the descriptive results, this negative influence is more pronounced for e-bike ownership than for c-bike ownership. For financially better-off households, there are positive coefficients for owning all types of bicycles, with the highest coefficient for owning a c-bike and an e-bike together. This indicates that households with low to medium income tend to purchase a c-bike first, while individuals in wealthier households are more likely to own an e-bike in addition to their c-bike.

Table 3. Average cycled kilometer related to bike ownership ($n = 188{,}900$).

	Mean daily distance (km)	
Ownership	Cycled	Driven
C- and e-bike	4.0	32.3
Only e-bike	2.5	28.4
Only c-bike	1.8	37.1
No bike	0.1	25.5
All	1.6	34.3

Table 4. Coefficients multinomial logit model for the bike ownership (Mc-Fadden R^2 = 0.101).

Reference:	No bike ownership	Only c-bike ownership	Only e-bike ownership	C-bike and e-bike ownership
Intercept		0.208***	−5.603***	−4.207***
Econ. status of the household (ref. = middle)	Very low	−0.113***	−0.853***	−0.564***
	Low	−0.168***	−0.639***	−0.398***
	High	0.441***	0.296***	0.623***
	Very high	0.502***	0.312***	0.808***
Living place (ref. = middle-sized town in an urban region or central city in a rural region)	Metropole	−0.082***	−0.824***	−0.729***
	City	−0.237***	−0.183***	−0.376***
	Provincial area in urban region	0.119***	0.146**	0.23***
	Middle-sized town or provincial area in a rural region	−0.123***	–	–
Gender	Male	0.232***	0.231***	0.26***
Age	Years >16	−0.057***	0.085***	−0.109***
	Years > 25	0.113***	–	0.227***
	Years > 40	−0.081***	−0.047***	−0.093***
	Years > 70	−0.059***	−0.157***	−0.146***
Driver's license ownership		0.585***	0.628***	0.84***
Car ownership	Every time	0.374***	0.527***	0.515***
	Sometimes	0.35***	0.345***	0.523***
Occupation	School student	0.998***	–	0.966***
	University student	0.998***	–	0.725***
	Employed	0.359***	–	0.252**
	Homemaker	0.176***	0.722***	0.443***
	Retired	0.177***	0.197***	0.335***
Public transportation pass		−0.057***	−0.669***	−0.244***

Significance codes: "***" 0 < Pr(>|z|) <0.001, "**" 0.001 < Pr(>|z|) < 0.01.

When analyzing the spatial level, coefficients for bicycle ownership are negative in metropolises and cities. Living in a metropolis has a substantial negative impact on owning an e-bike or both a c-bike and an e-bike. However, ownership of only a c-bike is much less influenced by this factor. This may be due to the lower benefits of e-bikes in densely populated cities, where public transportation options are typically more attractive, and the risk of bicycle theft is higher due to the limited availability of private garages. Furthermore, men have positive ownership coefficients for all types of bicycles.

The logit model uses stepwise linearization to create a function that considers an individual's age. (For instance, to calculate the age coefficient for c-bike ownership for a 30-year-old: $(30 - 16) \cdot -0.057 + (30 - 25) \cdot 0.113$). Figure 3 illustrates the resulting probabilities by age, considering the intercepts while holding the other covariates constant at their reference values. The probability of not owning a bicycle reaches a local maximum at the age 25, while the likelihood of owning at least one bicycle of any type is highest at the age of 40. After age 40, the probability of not owning any type of bicycle increases, particularly after age 70, which may be due to declining physical abilities. The probability of owning a c-bike follows the opposite trend. Age-related probabilities exhibit a similar pattern for e-bike ownership and for owning both a c-bike and an e-bike. They increase gradually until the age of 40, then rise more rapidly until the age of 70, and then decline again.

Although we have controlled for the other covariates, such as economic status, our data shows that both owning a driver's license or a car increases the probability of owning c-bikes and e-bikes. This finding challenges the expectation that e-bikes can replace car ownership. Additionally, owning a public transportation pass reduces the probability of owning a bicycle, with a much stronger effect on e-bikes and combined c-bike and e-bike ownership compared to c-bikes alone.

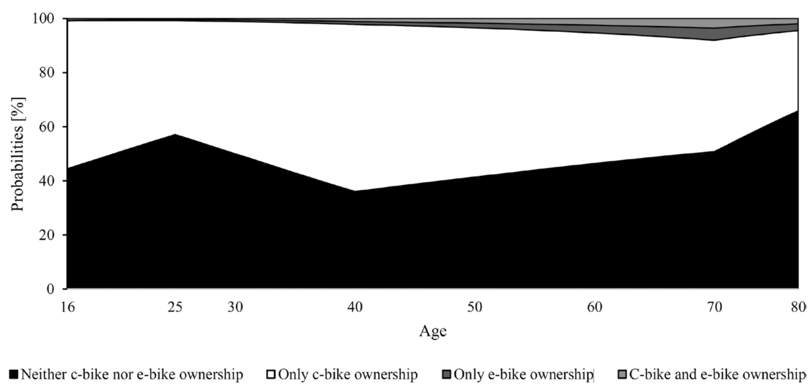

Figure 3. Probabilities for bike ownership related to age.

4.3. Descriptive analysis of c-bike and e-bike usage

At the trip chain level, this study considers the modes of walking, cycling, public transportation (PT), and motorized private transportation. For the latter, we use the term "car" in the following, as it is predominantly car-based. For the descriptive analysis, we use the dataset after filtering unclear values for potential factors of the logit model to be implemented later and consider only trip chains with a length of up to 50 km. The overall mode share distribution is displayed in Table 5 and shows that the car has a mode share of more than half, followed by walking, cycling, and PT.

Figure 4 displays the mode choice based on bicycle ownership and trip length. The cycling mode share is extremely low for individuals who do not own bicycles. For bicycle owners, the highest proportion of trip chains made by bicycle is for distances between 2 and 5 km. Beyond that distance, cycling shares decrease continuously. However, this decrease is less steep for the two groups with e-bike ownership than for those with only a c-bike. Therefore, individuals who own an e-bike make a higher proportion of longer trip chains by bicycle compared to those who only own a c-bike. Additionally, individuals who own an e-bike have higher overall cycling rates, which are even higher for those who own both an e-bike and a c-bike. For longer trip chains, the car remains the primary mode of transportation for all four groups, but the use of public transportation also increases with distance.

4.4. Multivariate analysis of mode choice

A second multinomial logit model analyzes the mode choice of individuals with multiple options. The final model includes variables for bicycle ownership, socioeconomic status, and situational factors. Additionally, the model includes interaction variables to evaluate the effect of socioeconomic and situational factors when paired with e-bike ownership. For instance, the model analyzes the impact of living in a metropolis combined with e-bike ownership. These coefficients are applied in addition, meaning that coefficients for metropolis and for metropolis and e-bike ownership both apply to e-bike owners. Table 6 presents the results.

Using the car as the reference category, the intercept is positive for walking and noticeably negative for PT. Male individuals are more likely to cycle. Figure 5

Table 5. Mode share ($n = 231{,}069$).

Mode	Share [%]
Walk	25.1
Cycling	13.2
PT	9.1
Car	52.6

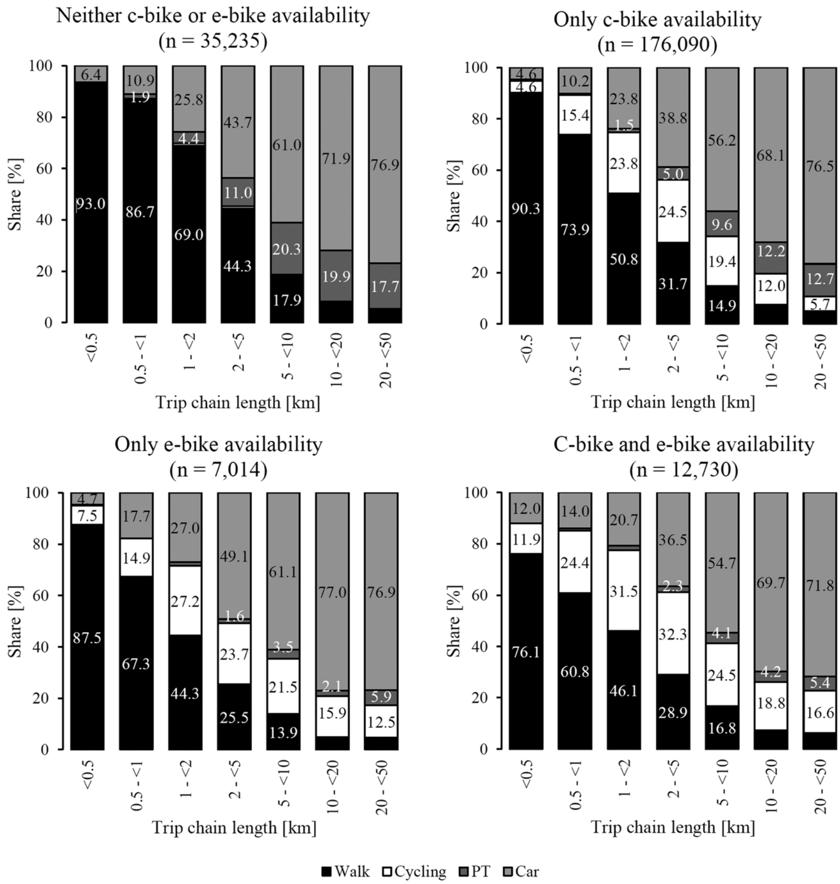

Figure 4. Mode choice related to trip chain length for different bike ownership.

displays the probabilities of mode choice based on age coefficients for a reference case with a trip chain length of 5 km. As age increases, individuals who solely own a c-bike are slightly less likely to choose the car mode. However, for e-bike owners, the probability of using the car decreases substantially, and the probability of cycling increases continuously with age and is one and a half times higher among older age people.

In metropolises and cities, the probability of choosing walking, cycling, or public transportation is generally the highest. However, owning an e-bike in a metropolis has a negative influence on cycling, possibly due to the higher risk of theft. Additionally, public transportation and cycling appear to be less attractive in rural areas than in urban areas. Owning a public transportation pass has a substantial positive impact on the use of public transportation and a smaller yet positive impact on walking and cycling.

Table 6. Coefficients multinomial logit model for mode choice (McFadden $R^2 = 0.318$).

Reference:	Car	Walking	Cycling	PT
Intercept		0.542***	–	−3.748***
Gender	Male	–	0.119***	–
Age	Years > 16	0.072***	0.01***	–
	Years > 16 and e-bike ownership	–	0.009***	–
	Years > 30	−0.088***	–	−0.01***
	Years > 50	0.025***	−0.012***	0.032***
Living place (ref. = middle-sized town in an urban region)	Metropolis	0.706***	0.92***	1.334***
	Metropolis and e-bike ownership	–	−0.562***	–
	City	0.367***	0.519***	0.61***
	Provincial area in an urban region or a central city in a rural region	0.122***	0.126***	–
	Middle-sized town or provincial area in a rural region	−0.249***	−0.289***	−0.745***
Public transportation pass		0.371***	0.403***	2.502***
Season (ref. = summer)	Winter	0.082***	−0.814***	0.159***
	Winter and e-bike ownership	–	−0.531***	–
	Spring	–	−0.286***	–
	Spring and e-bike ownership	–	−0.141**	–
	Autumn	–	−0.342***	–
	Autumn and e-bike ownership	–	−0.284***	–
Trip chain purpose (ref. = work and "other trip purposes")	Education	0.756***	0.64***	0.988***
	Business	–	−0.387***	−0.19***
	Business and e-bike ownership	–	0.919***	–
	Shopping	0.188***	−0.381***	−1.128***
	Private errands	0.615***	−0.238***	−0.574***
	Private errands and e-bike ownership	–	0.272***	–
	Leisure	2.04***	0.61***	−0.123***
	Leisure and e-bike ownership	–	0.221***	–
Trip length	- [km]	−0.78***	−0.286***	0.092***
	- and e-bike ownership [km]	–	0.027***	–
	Over 5 km [km]	0.551***	0.122***	−0.082***
	Over 10 km [km]	0.06***	0.11***	–

Significance codes: "***" 0 < Pr(>|z|) <0.001, "**" 0.001 < Pr(>|z|) < 0.01.

Mode choice depends on the season. Cycling is less likely in seasons other than summer, especially in winter. Additionally, individuals who own e-bikes are even less likely to cycle in autumn, spring, and particularly winter.

Education trips are associated with a lower likelihood of choosing the car mode. On the one hand, business trips are generally associated with a lower likelihood of cycling. On the other hand, the combination of e-bike ownership and business trip purpose has the opposite effect. The same is true for the trip purpose private errands. For leisure trip chains, there is a substantial increase

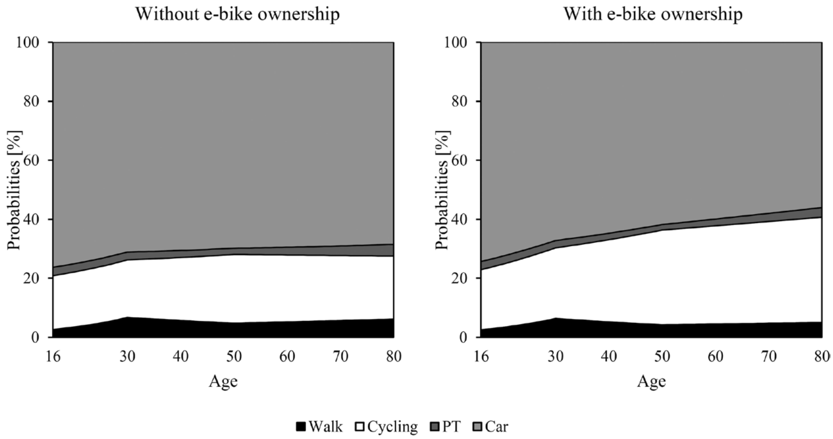

Figure 5. Probabilities for different modes by age for the reference case of a trip chain length of 5 km.

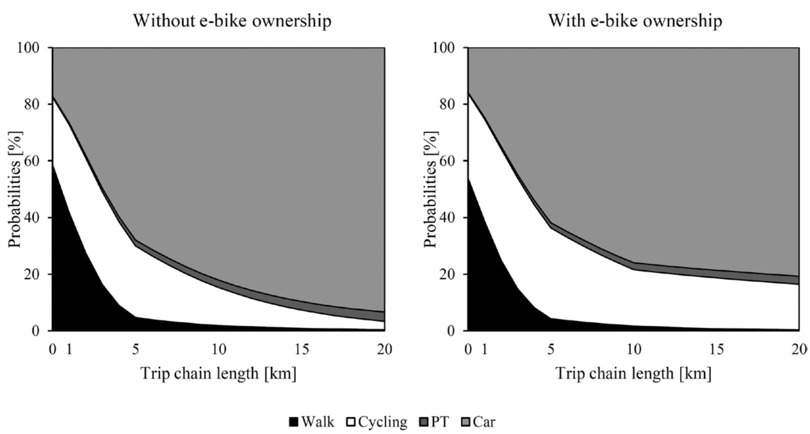

Figure 6. Probabilities for different modes related to trip chain length and e-bike ownership for a 50-year-old reference person.

in the probability of walking and a moderate increase in cycling. E-bike ownership further increases the likelihood of choosing cycling for trip chains with this purpose.

Figure 6 displays the probabilities of mode choice for a 50-year-old reference person based on the model coefficients for the trip chain length. The likelihood of walking decreases rapidly as the length increases from the first meter onward, while for cycling, this decline begins after 5 km. The proportion of cycling is higher for individuals who own an e-bike and remains significantly higher even for trip chains longer than 10 km. For longer distances, individuals are more likely to choose the car mode, while the probability of using public transportation remains low due to the geographic reference location and the assumption that the individual does not have a public transportation pass.

5. Discussion

5.1. Findings on e-bike ownership and usage

This paper investigates the relationship between e-bike ownership and travel behavior while controlling for age and socioeconomic status, addressing a gap identified by Bourne et al. (2020). The study confirms several previous findings, such as the age-dependency of e-bike ownership (Kroesen, 2017), and presents new findings on the relationship between age and e-bike usage. Kroesen (2017) reported a decrease in e-bike use with age, while our study found that e-bike ownership has an increasing positive influence with age. The higher ownership and use of e-bikes among older individuals may be attributed to the comfort of motor-assisted cycling, as physical and medical conditions are common reasons to purchase an e-bike (MacArthur et al., 2018).

Additionally, our research indicates that e-bike ownership depends on economic status, probably due to their higher purchase price compared to c-bikes. This finding is in line with previous research (Fishman & Cherry, 2016; Kroesen, 2017; Popovich et al., 2014). Consequently, e-bike ownership is primarily limited to older and more privileged individuals, raising concerns about equity. Furthermore, the model estimates that men are more likely to own c-bikes and e-bikes. In contrast, research has shown that women in the Netherlands own e-bikes more frequently than men (Kroesen, 2017; Plazier et al., 2023). Additionally, a study conducted in Norway by Fyhri and Fearnley (2015) found that e-bikes have a greater impact on women's cycling than on men's. Similarly, in the Dutch context, Sun et al. (2020) found that e-bikes extended the cycling range more for women than for men. In contrast, our model showed no significant influence on the probability of cycling based on the gender of the e-bike owner. Therefore, we excluded the variable.

Furthermore, there is no evidence to suggest that e-bikes are replacing car ownership. This result aligns with previous studies conducted in Germany and other countries (Ecke & Chlond, 2021; Kroesen, 2017), but it contradicts the findings of a study by Sun et al. (2020). In fact, the model suggests owning a car leads to an increase in e-bike ownership.

E-bikes are mainly owned outside of metropolises and cities, and while the probability of cycling is generally higher in metropolises, this is less pronounced for e-bike owners. This matches the literature finding that e-bikes are more useful in sparsely populated areas (Philips et al., 2022; Sun et al., 2020).

Furthermore, the trip purpose leisure has a significant additional influence on cycling among e-bike owners. This confirms the findings of MacArthur et al. (2018), who reported that leisure and recreational purposes were important reasons for e-bike purchases in the USA. However, this contradicts the findings of Castro et al. (2019).

Seasons with adverse weather conditions have a greater negative impact on cycling when individuals possess an e-bike compared to a c-bike. This finding challenges the conclusion by Kruijf et al. (2021) that e-bikes are less weather-sensitive because bad weather conditions, such as wind, affect e-bike use less due to motor support. However, our findings may be related to e-bikes as vehicles for seniors. One possible explanation for this is that e-bike owners have greater flexibility in choosing their mode of transportation or may choose not to make trips in inclement weather due to fewer work obligations. Sun et al. (2020) also used this argument to explain why people in their sixties cycled longer distances per trip and day with an e-bike than those in their fifties.

The study confirms that e-bikes serve as range extenders for the cycling mode (Castro et al., 2019; Sun et al., 2020). Previous research has identified higher travel speeds and reduced physical effort as reasons for this effect (Plazier et al., 2017). However, it is unclear whether passionate cyclists purchase an e-bike to make their long trips faster or whether people make longer trips by bicycle due to the benefits of an e-bike. Previous analyses have supported the finding of the range extender effect even after e-bike purchase (Plazier et al., 2017). However, it is unclear whether a self-selection bias influences this effect and whether it is generally applicable to individuals who do not own e-bikes.

Another question arises regarding the competition between public transportation and e-bikes. Kroesen (2017) found that e-bike owners use public transportation less frequently. Our results also show that owning a public transportation pass decreases the probability of owning an e-bike.

5.2. Methodological limitations and transferability

This paper presents findings on the transitional phase of the e-bike market take-up in Germany. The results may be relevant for other countries with lower e-bike shares that are currently in or entering a similar phase in the near future. Infrastructure, settlement patterns, topography, cycling rates, and cycling infrastructure quality vary among countries, as well as e-bike market penetration and regulation. Therefore, differences in e-bike use between Germany and other locations are unsurprising. This emphasizes the challenges of transferring research results from one country to another. Conducting country-specific research on this topic is therefore crucial. Even within countries, different legislations on e-bike types can exist, such as in the USA (MacArthur & Kobel, 2017), making generalizations difficult. Standardized categories would be useful for facilitating international comparisons, particularly when using household travel surveys, as these typically use local regulations to categorize bicycle types. Apart from that, country-specific subscription models for e-bikes and the provision of e-bikes by companies to their employees as part of their salary can make comparisons more challenging due to their dependence on tax laws. Furthermore, differences in e-bike market penetration among countries lead to varying distributions of e-bikes among socioeconomic groups, resulting in diverging patterns of e-bike use.

Our analysis identifies the factors that influence bicycle ownership and mode choice. However, the analysis of household travel surveys cannot explain the reasons behind these factors. Therefore, further analysis of longitudinal data is advisable, especially as e-bikes become more widespread.

The data collection for this analysis took place in 2016 and 2017. It is worth noting that the number of e-bike owners, the e-bikes themselves, and general mobility behavior since then have changed, mainly due to the COVID-19 pandemic. While we believe that the results of this study reflect the pre-COVID situation relatively well, it is likely that some results will differ with newer data. In 2023, Germany conducted a new national travel survey that provides an updated picture of e-bike ownership and use. The data will reflect the establishment of e-scooter sharing schemes and other microelectric vehicles, as well as a significant increase in the share of s-pedelecs.

This paper employs multinomial logit models as an approach for discrete choice modeling. To incorporate clustering effects within households, other approaches such as multilevel models could also be used. Nevertheless, the results of our study add to the overall understanding of the impact of e-bikes on mobility, as they differ somewhat from the findings of studies conducted in other countries.

6. Conclusion

This paper estimated the factors that influence e-bike ownership and usage in Germany. The study found highly significant coefficients for several relationships using an extensive dataset. The results confirmed previous findings on e-bike ownership and use in other countries while also revealing new insights and contradictions. The study found that e-bike ownership is more prevalent among older individuals with higher wealth, raising equity concerns. E-bikes also increase the mode share of cycling, particularly among older age groups. Although the peak of bicycle ownership is between the ages of 40 and 50, e-bike ownership peaks at 70. E-bikes expand mobility options and promote health by encouraging cycling among this age group, making them a tool for improving the quality of life. However, e-bike ownership increases cycling mode share less among young people, which contradicts previous research. Ownership of both c-bikes and e-bikes declines after the age of 70. However, for those who possess an e-bike, the likelihood of cycling remains high.

It is uncertain whether e-bikes can significantly improve the sustainability of mobility behavior, particularly for work-related trips, as most owners are at or near retirement age. Furthermore, there is a noteworthy negative coefficient for e-bike ownership on cycling during bad weather seasons.

In contrast, our results support the thesis that e-bikes serve as a range extender, keeping the cycling mode share higher even for trips longer than 10 km, and substantially increasing the cycling mode share. Our findings support the claim that e-bikes are primarily purchased and used for leisure trips. However, they are mostly owned in rural areas where public transportation is less accessible, indicating that cars are the main alternative mode of transportation. The range extender effect supports the argument that e-bikes can contribute to greater sustainability. In summary, while there are evident benefits of e-bikes for transportation planning in Germany, there are also some drawbacks to consider. For example, their use is more seasonal, and there is no evidence that they replace car ownership.

Nevertheless, public authorities could promote the market penetration of e-bikes through subsidies similar to those for electric cars or by supporting e-bike subscription models. Depending on the design of such subsidies, they could increase e-bike ownership for individuals from lower-income households. This would address equity issues, as our study found that those individuals have lower access to e-bikes. Furthermore, secure parking is crucial for e-bikes due to their high purchase price. While wealthier households in single-family homes typically have better storage options, poorer households living in shared buildings often lack adequate storage for e-bikes. To reduce barriers to owning and using e-bikes, it is crucial to provide secure bicycle parking in public areas and incorporate bicycle parking into building codes. Furthermore, it is probable that an overall increase in cycling infrastructure could promote both conventional and e-bike cycling.

Apart from that, policymakers could address some barriers to the adoption of e-bikes. Firstly, companies providing charging infrastructure and electricity to their employees and customers should not face tax issues, as is currently the case in Germany. Additionally, standardization of charging equipment is still lacking, requiring e-bike owners to bring the corresponding charger with them when they need to recharge during a trip chain. According to our research, the season has a greater impact on the likelihood of e-bike owners cycling compared to c-bike owners. It may also be useful to provide special public transportation passes as a backup for cyclists during inclement weather seasons to encourage cycling.

However, it is unclear how the increasing diffusion of e-bikes among the population affects their usage patterns. The perception of e-bikes in Germany is evolving. Once viewed as a mobility option for retired individuals with limited physical abilities, working-age individuals are now also considering e-bikes as a means to expand their mobility options. Furthermore, the COVID 19-pandemic and the rise of e-scooters, particularly in sharing systems, have influenced mobility behavior. Therefore, it would be interesting to repeat this analysis with future data based on a broader diffusion of e-bikes in the population.

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Authors contribution

The authors confirm their contribution to the paper as follows: Research, analysis, and interpretation: David Kohlrautz. Supervision and advisory: Tobias Kuhnimhof. All authors reviewed the results and approved the final version of the manuscript.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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