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Electric Bicycles and Public Transport Tickets: Ownership and Car Use Patterns

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Abstract

Riding electric bicycles and using public transport are popular alternatives to private car use. Utilizing data from a 2022 survey of 6,285 participants in Germany, we examine who typically owns e-bikes or public transport tickets. We firstly employ regression analyses to identify correlations between individual characteristics and e-bike as well as ticket ownership, respectively. We find that e-bike owners tend to be older, earn higher incomes, and often reside in more rural areas. For public transport ticket ownership, these associations are largely reversed. Through latent class analyses, we identify distinct groups of e-bike and ticket owners. In a second step, we investigate associations between e-bike or ticket ownership and several car use measures through propensity score matching and regression analyses. We find that, compared to non-owners, owners of either alternative exhibit lower car use, with the difference being larger for public transport ticket owners.

Key words: E-bike (Electric bicycle), Public transport, Travel mode choice, Car use, Latent class analysis, Propensity score matching

JEL codes: L92, R22, R41

1. Introduction

Since 1990, CO_2 emissions in Germany have decreased by about 40% overall, while emissions from the transport sector specifically have decreased by less than 10% (UBA, 2023a; UBA, 2023b). Germany has a particularly high rate of motorization with 47% of trips traveled by car or other individual, motorized vehicles, such as motorcycles, while trips made by public transport and by bicycles only accounted for 10% and 17%, respectively (Ecke et al., 2023). In addition to CO_2 emissions, travelling by car also creates other negative externalities such as road accidents, congestion, noise, and air pollution (Zheng et al., 2010; Schmutzler, 2011; Wilhelm et al., 2012; Adler and Ommeren, 2016). Shifting to alternative modes such as public transport and (electric) bicycles can hence decrease the cumulative adverse health effects and externalities from individual car travel as well as cause markedly fewer CO_2 emissions (e.g., Schmutzler, 2011; Adler and Ommeren, 2016; UBA, 2021; UBA, 2023c).

A behavior shift towards greener modes of transport can be motivated through policy along different avenues. In order to use a transport mode, individuals first of all must have (or purchase) access to this mode, through ownership of the respective vehicle, or through a ticket that allows boarding. In this study, we therefore look closer at ownership patterns of e-bikes and of public transport tickets and the correlations between ownership and car usage.

We chose to focus on the ownership of e-bikes and public transport tickets because we presume these to be the most promising sustainable alternatives, providing owners with the opportunity to replace car use. While tickets have long been a common and obvious alternative to car driving, e-bikes specifically are a newer addition to mobility options, are now becoming increasingly wide-spread, and provide the ability to cover larger distances than regular, non-electric bicycles. Due to their rather recent rise in popularity, there is still ample need for research on both the factors that determine e-bike ownership as well as its potential to replace car use. Both modes are used by – and owned by – a substantial proportion of the population, which is not the case for several other, newer mobility modes, such as micromobility options like e-scooters. While any mode can gain from targeted policy interventions, both purchasing an e-bike and holding a public transport ticket are expensive and may thus benefit especially from promotional polices. Here, it may be beneficial to identify current and potential future user groups to the ensure efficient use of public funds.

For our study, we use data from a large-scale, nation-wide survey conducted with a total of 6,285 participants from Germany. The data were collected in cooperation with the market research and opinion polling institute *forsa* in the spring of 2022. Amongst the survey participants, there are 1,572 e-bike owners (25%) and 1,230 (20%) hold a public transport ticket. With our study we want to supply a thorough, up-to-date description of e-bike and public transport ticket owners and their characteristics, and define easily identifiable sub-groups. We also aim to find out how ownership and thus access to these two alternative modes of transport is correlated with car usage and whether this differs between identified subgroups. Overall, we intend for our study to be a reference for potential new policy.

In the first part of this paper, we aim to find common characteristics of e-bike and ticket owners and employ linear probability model (LPM) regressions[1] with potential determinants of ownership as explanatory variables, which are largely based on findings from the literature. We then investigate if distinct groups can be identified within the sub-samples of e-bike and public transport ticket owners, respectively. Similar to de Haas et al. (2022), we use latent class analyses (LCAs) and do so separately for both modes of transport. In the second part of the paper, we are interested in how e-bike or ticket ownership correlates with car use. To account for the non-random allocation of transport alternatives across the population, we use regression analyses with adjustment for covariates as well as propensity score matching (PSM) methods. To thoroughly examine this relationship, car use is measured in four different ways, namely, weekly car use frequency in number of trips and in kilometers, total kilometers driven by the households' cars in a year, and whether a car is used as the primary mode of commuting. Our findings corroborate previous studies regarding the characteristics for e-bike and ticket owners for the German sample: E-bike

[1] LPM are ordinary least squares (OLS) estimations that use dichotomous variables on the dependent side.

owners are, on average, older, earn higher incomes, and are more likely to reside in rural areas, whereas public transport ticket owners are, on average, younger, earn lower incomes, and reside in urban areas. Both groups self-report a tendency for Green voting preferences. Ticket owners also show lower car use compared to non-owners. While this is also the case for e-bike owners, the difference is much smaller here. Through LCA, we identify sub-groups of owners and observe varying levels of car use within these groups. Overall, our results on e-bike and ticket owner characteristics and sub-groups can facilitate policy targeting by highlighting demographic disparities in ownership and in car use behavior.

We make several unique contributions to the literature. First, our large, nation-wide survey data enables us to get a thorough overview of e-bike and public transport ticket owners across a sample that is largely representative of the general population. We thereby also include those respondents who may not be present in studies that use more specific or smaller samples. Our sample is an order of magnitude larger than most other current studies on either e-bike or public transport ticket ownership. Second, as far as we know, it is the first large-scale study on e-bike ownership which does not focus on early adopters and includes non-owners as the comparison group. Third, we analyze correlations between e-bike or public transport ticket ownership and car use in depth, by looking at four different measures and by implementing PSM for better comparability to non-owners.

In section 2, we give a detailed overview of the current literature on e-bike ownership, public transport ticket ownership, and their connections to car usage. Section 3 describes our sample. Section 4 then comprises our results on the characteristics of owners as well as the LCA for both groups, followed by section 5, which presents and discusses our results on the correlations between ownership and car use. Section 6 concludes.

2. Literature Review

2.1. Current Policy, Usage, and Ownership Patterns - E-Bikes

E-bikes have become more popular especially over the past decade and allow their users to ride longer distances and with less effort compared to regular, non-electric bicycles (Statista Research, 2023). In Germany, 2.1 million e-bikes were sold in 2023, which sums up to an estimated total of 11 million e-bikes (ZIV, 2024). E-bike usage in Germany has increased slowly but steadily, with the share of trips made by e-bikes at 4% in 2022 (Ecke et al., 2023). Since October 2024, the government has been subsidizing the purchase of e-cargo bikes, but only for companies and organizations and not for individuals (Bundesamt für Wirtschaft und Ausfuhrkontrolle, 2025). Several incentive programs for individuals are currently available to increase the adoption of, mostly, e-cargo bikes in Germany, albeit primarily locally, through regional programs. For example, the cities of Stuttgart and Munich offer monetary incentives for individuals purchasing e-cargo-bikes and, in the case of Munich, charging ports (Stadt München, 2025; Stadt Stuttgart, 2025). For regular e-bikes, local energy providers in cities such as Marburg and Tübingen subsidize e-bike adoption (Stadt Marburg, 2025; Stadt Tübingen, 2025). There are also bike sharing services that have added e-bikes to their offers, but only in a limited capacity in a handful of regions (e.g., DB InfraGO AG, 2025; nextbike, 2025; Rheinisch-Bergischer Kreis, 2025). Other European countries do not have nation-wide incentive programs either but also often offer regional monetary incentives (European Cyclists Foundation, 2025). The French government subsidizes e-bike purchase depending on individual income (Ministère de l'Économie, des Finances et de la Souveraineté industrielle et numérique, 2025), while employees in the Netherlands can receive tax credits for leasing an e-bike from their company and they are allowed to use them for non-work related rides (Rijksoverheid, 2025). Similarly, there are scattered schemes for e-bike adoption in the United States and Canada (Transportation Research and Education Center, 2022). According to results from a study evaluating the effectiveness of such financial incentive programs in Norway, adopting an e-bike while receiving a subsidy could induce a modal shift decreasing car use (Sundfør and Fyhri, 2022).

Due to the only recent popularity of this mode of transport, previous research on the motivations for purchasing an e-bike and the individual characteristics of e-bike owners is sparse. Such studies usually rely on individual-level survey data of early e-bike adopters from selected regions. It has been shown that e-bike owners are, on average, older than the general population, often retired, are more likely to be located in rural than in urban areas, care about the environment, and intend to overcome longer distances than with regular bicycles (Popovich et al., 2014; Wolf and Seebauer, 2014; Jones et al., 2016; Şimşekoğlu and Klöckner, 2019; Reck et al., 2022; Mina et al., 2024; Philips et al., 2024; Yin et al., 2024). A ruling opinion on the relationship between e-bike ownership and distance to destinations such as the workplace has not been established yet as researchers find conflicting results (Wolf and Seebauer, 2014; Astegiano et al., 2015; Bigazzi et al., 2025). There has been no consensus on the predominant gender of e-bike owners. While some studies find no statistical effect of gender on e-bike purchase or ownership (Jones et al., 2024; Mina et al., 2024), others discover that men cycle more than women (Wu et al., 2024).

For income, Jones et al. (2024) find that respondents in the United States with a higher income are more likely to purchase an e-bike, while around 40% of households in Wuhan, China in the lowest income groups own at least one e-bike (Sun et al., 2024), suggesting that differences in culture, built environment and use purpose of e-bikes may influence ownership. E-bikes were also found more frequently in larger households and the presence of children under the age of 12 is positively associated with purchasing and owning any type of bicycle, while its relation with e-bike ownership remains unclear (Şimşekoğlu and Klöckner, 2019; Ren et al., 2024; Wu et al., 2024; Jones et al., 2024). For Germany specifically, a recent study by Poier et al. (2025) which focuses on personality traits and life satisfaction of e-bike owners finds positive correlations between e-bike ownership and age, higher income, worrying about climate change, and life satisfaction.

Overall, the literature seems to show some consensus on correlations between e-bike ownership and higher age, higher income, and environmental consciousness. Factors for which conflicting results have been found were gender and distance to the workplace as well as other destinations. In a study Haas et al. (2022) examined e-bike use in the Netherlands and identified five groups of characteristic users. The largest group, which makes up more than half of the e-bike users surveyed, are retired and use their e-bikes for leisure purposes. The second largest group consists of middle-aged full-time workers, while the third largest group contains older, female leisure users. Young, part-time working women and students make up the two smallest groups (Haas et al., 2022).

2.2. Current Policy, Usage, and Ticket Ownership Patterns - Public Transport

Regarding public transport tickets, there have been important recent developments in Germany. From June to August 2022, the German government has temporarily incentivized the purchase of public transport tickets with the introduction of the *9-Euro-Ticket*, which allowed ticket owners, per monthly subscriptions of only 9 Euros, to use regional German public transport. Studies on this three-month period find that especially households with lower income benefited from this offer, while its overall impact on car use was limited (Adenaw et al., 2022; Andor et al., 2022; Hille and Gather, 2022). In May 2023, the *Deutschlandticket* was introduced and continues to offer nation-wide access to regional public transport for a starting price of 49 Euros, currently priced at 58 Euros, which is cheaper than previous, regular subscription-based fares. Another reduction on regular ticket subscription prices is the *Semestertickets*, which have long since offered students inexpensive commuting options to school or university, simultaneously encouraging sustainable mobility (Blees et al., 2001; Bamberg et al., 2003; Müller, 2010).

On the topic of public transport tickets, prior research is more abundant and covers a wider variety of owner characteristics. Previous research on public transport tickets has shown that ownership decreases with age, women are more likely to own a ticket, users mainly live in urban areas, and environmentally friendly norms are prevalent among ticket owners (Simma and Axhausen, 2001; Matthies et al., 2002; Bamberg et al., 2007; Buehler, 2011; Giesel and Köhler, 2015; Busch-Geertsema et al., 2021; Reck et al., 2022). Ticket ownership also depends on income and profession as the use generally decreases with income but increases with commuting distance (Buehler, 2011; Giesel and Köhler, 2015; Busch-Geertsema et al., 2021; Kersting et al., 2021). There seems to be overwhelmingly consensus on the characteristics correlated with public transport ticket ownership. There are no current studies which specifically group the *owners* of public transport tickets via LCA or other approaches. Regarding *users* of public transport, there are several studies which employ LCA but focus on psychological aspects and attitudes of users (Choi et al., 2021; Vallée et al., 2024). They show that personal norms, personality, and environmental attitudes are important drivers of public transport use. Rafiq and McNally (2021), on the other hand, identify user groups in the United States by socioeconomic characteristics and focuses on their usage patterns. The groups identified by their LCA approach differ by gender, ethnicity, and age, and most groups use public transport predominantly for work-related trips. A detailed summary of prior research on e-bike and ticket ownership can be found in the Appendix (Tables A1 and A2).

2.3. Relationship of Ownership with Car Use

Regarding the relationship between e-bike or ticket ownership and car use, there is only little research, which may be due to the difficulties in identifying causal effect directions. Some existing findings in the empirical literature diverge and, in particular, it remains unclear whether e-bikes merely replace normal bicycles and whether they are used for leisure or commuting purposes (Wolf and Seebauer, 2014; Astegiano et al., 2015; Simşekoğlu and Klöckner, 2019; Sun et al., 2020; Söderberg et. al. 2021; Haas et al., 2022; Jones et al., 2024; Yin et al., 2024). Studies in Europe, North America, and Australia also find that car owners are also likely to own an e-bike and that these e-bike owners at least state that they use their car less (Wolf and Seebauer, 2014; Astegiano et al., 2015; Jones et al., 2016; Simşekoğlu and Klöckner, 2019; Philips et al., 2024; Ren et al., 2024). For a sample of households in China, Sun et al. (2024) present that e-bike and car ownership are negatively associated, while Bigazzi and Wong (2020) show that for studies in China, owning an e-bike rather substitutes public transport use than car use.

Research on correlations between public transport and car use is less ambiguous, concordantly finding that public transport can replace car use in certain contexts (Steg, 2003; Jou and Chen, 2014; Şimşekoğlu et al., 2015; Busch-Geertsema et al., 2021; Schaefer et al., 2021). Table A3 in the Appendix summarizes previous findings on the effect of ownership of e-bikes or public transport tickets on car use in more detail.

3. Data

The survey data were collected as part of a research project funded by the *Stiftung Mercator* on individual mobility behavior and attitudes towards transportation policy measures in spring 2022. The survey itself was designed by the RWI – Leibniz Institute for Economic Research in Germany and data were collected by the market research and opinion polling institute *forsa*, which administers an online panel (forsa.omninet). The panel is representative of the German-speaking population in Germany aged 14 and above who use the Internet. Panel members are recruited by *forsa* via telephone, which ensures that individuals who seldom use the internet can also participate in the surveys. There is no option to actively apply for participation in the panel or surveys which avoids self-selection and minimizes the risk that the sample primarily consists of individuals particularly interested in the topic or of survey bots. For our study, only participants aged 18 and above were invited to take part in the survey. The final sample consists of 6,285 participants who completed the survey.

Table 1 contains descriptive statistics of our sample, including socioeconomic characteristics as well as other variables relevant to our analyses, such as the place of residence, environmental attitudes and car use. In Table A4 in the Appendix we show our sample's distribution regarding age, gender, highest level of education, household net income, and household size and compare them to the most recent German *Mikrozensus* which is representative of the German population (Statistisches Bundesamt 2024a; 2024b; 2024c). It shows that our sample is largely representative, but skews slightly toward being older, being better educated, earning higher incomes and living in smaller households as compared to values found in the *Mikrozensus*. Further, there are more men (54%) than women in our sample.

In total, 1,572 respondents indicated that their household owns at least one e-bike and 1,230 individuals reported that they own a ticket for public transport, making up 25% and 20% of our sample, respectively.[2] 238 respondents (4%) own both an e-bike and a ticket, while 3,696 (59%) own neither. Tables A5 and A6 provide further details on the distribution of e-bike and ticket ownership of the respondents across a number of descriptive variables. We also provide additional information on the distribution of e-bike and ticket owners by age group (Tables A8 and A9), by respondents' distance to the workplace (Tables A10 and A11), and by German federal state (Bundesland) (Tables A12 and A13).

For our study, we have purposefully chosen to focus on ownership characteristics, since ownership is a prerequisite for usage, and should be equally a focus of policy interventions as usage behavior. The two are naturally linked, which we can show is the case for our data, to a certain extent. For e-bike use, our data unfortunately only includes usage data of e-bikes and regular bikes as a sum, but even just looking at this combined use, 56% of or sample's e-bike owners used a bike or e-bike in the last 7 days, while only 25% of non-owners did (Table A14). Similarly, 65% of the owners of public transport tickets in our sample used public transport in the past 7 days, while only 8% of non-owners did (Table A15). Regarding other alternative mobility options not explicitly included in the remainder of this study, e-scooter ownership within our sample amounts to 3% among e-bike owners and less than 2% among ticket owners and those without e-bikes or tickets. Around 71% of participants own regular bicycles, and this ownership does not correlate with that of e-bikes or public transport tickets. Only 5.9% of participants in our sample state that their household owns an electric car. Among households with e-bikes, electric car ownership is a bit more likely with 9.2%. Among ticket owners, only 3% own an electric car.

Throughout this paper, we generally understand public transport ticket ownership not as the occasional purchase of single-journey tickets but as holding permanent or seasonal passes, which are often subscription-based, or, at least, tickets that are valid for a certain period of time or for multiple trips. The exact wording for all questions can be found in the Appendix. It should further be noted that some variables are collected on the individual level, such as age, gender and ticket ownership, while other variables are collected on the household level, such as income, e-bike ownership and total annual kilometers driven by car (Table 1). Despite our object of analysis - owners of e-bikes or tickets - being at the individual level, we choose to employ variables both at the household and at the individual level. The reason for this is that the variables measured at the household level, specifically income, ownership of cars, and ownership of e-bikes, can reasonably be assumed to influence any individual in the household, even if the person answering our survey is not the primary income earner or the main user of the car or e-bike, respectively. These variables are often measured at the household level and not at the individual level, as can also be seen in the German Socio-Economic Panel (SOEP) (see, for example, Poier et al. (2025)). Additionally, ownership decisions, especially of cars and e-bikes, which are expensive, are often made at the household level. We make sure to take the different levels of measurement into account in our interpretations. Additionally, for brevity and ease of reading, when we speak of "e-bike owner", we mean "individual in whose household an e-bike is present".

4. Characteristics of E-Bike and Public Transport Ticket Owners

In the first step, we aim to find individual characteristics that are associated with e-bike and ticket ownership. For this purpose, we use linear probability model (LPM) regressions with ownership of e-

[2] It should be noted that at the time of data collection, neither the *9-Euro-Ticket* nor the *Deutschlandticket* were introduced yet in Germany.

Table 1: Descriptive statistics of survey sample (N = 6,285)

Variable	Mean	Std.D.	Min	Max	Information
E-bike ownership (d)	0.25	-	0	1	1 if at least one e-bike in household
Ticket ownership (d)	0.20	-	0	1	1 if owning public transport ticket
Car ownership (d)	0.90	-	0	1	1 if at least one car in household
Car use frequency	7.67	7.65	0	99	Frequency of car use in the last seven days (capped at 99)
Weekly distance by car	124.97	142.98	0	670.00	Distance traveled by car in the last seven days in km (top 5% winsorized)
Yearly distance by car	8,380	6,747	0	110,000	Sum of total annual km traveled by all (up to three) cars in household and divided by number of adults (top 5% winsorized)
Car to commute (d)	0.60	-	0	1	1 if car is primary mode of transport to commute (to work, school, university)
Age	56.20	15.79	18	99	Age
Male (d)	0.54	-	0	1	Gender (1 if male)
University degree (d)	0.26	-	0	1	Education (1 if university degree)
Income	3,450	1,500	350	15,000	Net monthly household income in Euros (capped at 15,000)
Income (equivalized)	4.62	1.81	0.19	13	Equivalized income in categories (c.f. Eurostat, 2024), factor 1 for first, 0.5 for additional adult member, 0.3 for children
Working (d)	0.55	-	0	1	1 if (self-)employed / working
Single household (d)	0.27	-	0	1	1 if only one adult in household
Children (d)	0.16	-	0	1	1 if children under 14 years old in household
City (d)	0.32	-	0	1	1 for city (at least 100.000 inhabitants)
Town (d)	0.38	-	0	1	1 for town (less than 100.000 inhabitants but not village)
Rural (d)	0.30	-	0	1	1 for villages or rural
Vote Green Party (d)	0.17	-	0	1	1 if in favor of Green Party
Climate change conseq. (d)	0.67	-	0	1	1 if climate change perceived to negatively affect respondent in the future
Self-assessed env. behavior	3.33	0.78	1	5	Self-assessed environmentally conscious behavior, scale from completely disagree (1) to completely agree (5)
Distance workplace	19.09	22.13	0	190.00	Distance workplace in km (top 1% winsorized)
Distance public transport	0.82	0.99	0	9.00	Distance to nearest public transport stop in km (top 1% winsorized)

Note: (d) stands for dichotomous variable bikes or public transport tickets as dichotomous dependent variables, respectively. Our models estimate the following equation:

$$ownsalternative_i = \beta_0 + \beta_x \cdot X_i + \epsilon_i \quad (1)$$

where $ownsalternative_i$ is the binary ownership variable for an individual i, for e-bike or public transport ticket, respectively, X_i represents the covariates, i.e., the variables we suspect to be relevant to ownership, and ϵ_i is the error term. Since our dependent variable is binary, the estimated coefficients can be interpreted as effects on the likelihood of owning an e-bike or ticket.

For each of our two transport options, we estimate two models: The general model (1), and the commuters' model (2). The general model includes the standard socioeconomic characteristics age, age squared, gender, education, and income as well as status of employment, whether there is only one or more adults in the household, the presence of younger children in the household, car ownership, the place of residence, the respondent's voting preference, their climate change-related attitudes, self-assessed environmentally conscious behavior and the distance to the nearest public transport stop. For the commuters' model, we only include participants who are currently employed or are students, and we add the covariate of distance to the workplace or educational institution. The distance to the nearest public transport stop is expected to be primarily relevant for the ownership of tickets, but is added to both models to ensure comparability. To avoid disproportionate effects of outliers, the distance variables are winsorized at the top 1% and then logarithmized.

Complementary to the regression results, a simple comparison of mean socioeconomic and other relevant characteristics between owners and non-owners of the two respective transportation alternatives can be found in the Appendix (Tables A5 and A6). Further, given the dichotomous nature of the dependent variable, we also estimated all our models using a logit estimator. The results from these estimations can be found in Table A16 and do not notably differ from the results of our LPM estimations. For simplicity and easier interpretability of coefficients, we chose the LPM regression results over the logit regression ones to be shown here as main results.

4.1. LPM: Characteristics of E-bike and Ticket Owners

Table 2 shows the results of regressing e-bike ownership and public transport ticket ownership on the above-mentioned sets of covariates. In the general model (1) for e-bike ownership - shown in the first column - higher age, higher income, voting for the Green Party, and higher self-assessed environmental consciousness are statistically significantly and positively correlated with e-bike ownership, while living alone and living in a city or a town, as opposed to in a smaller village, are negatively correlated with ownership. This corroborates the, in comparison, low rates of e-bike ownership found for the large cities of Berlin and Hamburg (see Table A12). There is no statistically significant association with the employment status or with the perception of climate change consequences. The probability of owning at least one e-bike increases with age. Table A8 shows that ownership is highest among those aged 60 to 69 and then declines again in older age brackets.

Adding the distance to work variable in the commuters' model (2) reduces the number of observations as it focuses on participants who work or visit an educational institution. In this model, several variables which were statistically significantin the previous one are not significant anymore. The distance to the workplace shows a statistically significant negative correlation with the likelihood of owning an e-bike. Table A10 reveals only little variation in e-bike ownership across different distance brackets to the workplace. Slightly lower rates can be observed for distances larger than 25 km. Overall, based on the estimation results reported in Table 2, the most predictive factors for owning an e-bike seem to be age, household structure and the location of residence.

It is intuitive that e-bikes are more popular among older respondents since they are more convenient than regular bicycles. The higher price of e-bikes compared to regular ones also explains the correlation with higher incomes. Importantly, since there is no (negative) correlation between car and e-bike ownership, owning an e-bike does not seem to be a substitute to owning a car. This could be related to e-bike

Table 2: LPM results on e-bike or public transport ticket ownership

	E-bike ownership				Ticket ownership			
	(1) general		(2) commuters		(3) general		(4) commuters	
	Coeff.	Std. E.	Coeff.	Std. E.	Coeff.	Std. E.	Coeff.	Std. E.
Age	0.012**	(0.003)	0.004	(0.005)	-0.016**	(0.002)	-0.010*	(0.004)
Age squared	-0.000**	(0.000)	-0.000	(0.000)	0.000**	(0.000)	0.000*	(0.000)
Male (d)	0.013	(0.012)	-0.010	(0.016)	-0.023*	(0.010)	-0.025	(0.013)
University degree (d)	-0.026	(0.014)	-0.021	(0.019)	0.023	(0.012)	0.033*	(0.016)
Income (equivalized)	0.011**	(0.004)	0.008	(0.005)	-0.002	(0.003)	-0.003	(0.004)
Working (d)	-0.024	(0.018)	0.009	(0.052)	-0.025	(0.015)	-0.421**	(0.044)
Single household (d)	-0.129**	(0.014)	-0.131**	(0.020)	0.002	(0.012)	0.008	(0.017)
Children (d)	-0.037*	(0.018)	-0.012	(0.020)	-0.031*	(0.015)	-0.010	(0.017)
Car ownership (d)	0.040	(0.023)	0.035	(0.032)	-0.325**	(0.019)	-0.313**	(0.027)
City (d)	-0.108**	(0.016)	-0.108**	(0.021)	0.215**	(0.013)	0.209**	(0.018)
Town (d)	-0.057**	(0.015)	-0.071**	(0.019)	0.016	(0.012)	0.034*	(0.016)
Vote Green Party (d)	0.034*	(0.016)	0.008	(0.021)	0.054**	(0.013)	0.063**	(0.017)
Climate change conseq. (d)	0.004	(0.013)	-0.003	(0.018)	0.036**	(0.011)	0.036*	(0.015)
Self-assessed env. behavior	0.039**	(0.008)	0.031**	(0.010)	0.007	(0.007)	0.003	(0.009)
Distance public transport	-0.015	(0.030)	0.040	(0.039)	-0.070**	(0.024)	-0.078*	(0.033)
Distance workplace			-0.025**	(0.009)			0.030**	(0.007)
Constant	-0.158	(0.084)	0.038	(0.124)	0.937**	(0.069)	1.050**	(0.103)
# Observations	5,165		2,924		5,184		2,931	
Adjusted R-Squared	0.05		0.04		0.20		0.23	

Note: (d) stands for dichotomous variable
Dependent variables are dichotomous ownership of e-bike (1), (2) or dichotomous ownership of ticket (3), (4)
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

owners living in more rural areas, where people often need cars to drive longer distances. It also indicates that e-bikes may be used more for leisure than for commuting or other regular trips. Indeed, in a simple comparison of means, car ownership rates are higher among e-bike owners than among non-owners (Table A5), but with car ownership showing no significant association in the LPM model, it seems that other factors, such as the location, may be primarily predictive of both e-bike and ticket ownership. The variable for employment status did not show any significant correlations with e-bike ownership. This could mean that age, rather than the retirement status, seems to be the relevant factor for e-bike ownership. Voting for the Green Party and self-reported environmentally conscious behavior are two further factors with a positive significant association with e-bike ownership. It is unclear, though, whether environmental consciousness drives purchasing decisions for e-bikes, or whether e-bike owners perceive themselves as more environmentally conscious due to owning and using a transportation mode that is seen as sustainable. Further, given the variable's subjective nature, there may exist differences in how critically participants assess their behavior towards the environment.

Overall, these characteristics of e-bike owners largely align with those found by previous studies on age (Wolf and Seebauer, 2014; Şimşekoğlu and Klöckner, 2019; Sun et al., 2020; Philips et al., 2024; Poier et al., 2025), high ownership of cars (Wolf and Seebauer, 2014; Şimşekoğlu and Klöckner, 2019; Ren et al., 2024), pro-environmental attitudes (Popovich et al., 2014; Şimşekoğlu and Klöckner, 2019; Mina et al., 2024), and higher income (Jones et al., 2024; Poier et al., 2025). Correlations with having children were slightly negative in our sample, while the literature was ambiguous (Jones et al., 2024; Ren et al., 2024). Correlations with distance to work were negative here, while in the literature a large distance is sometimes cited as a reason for, or being correlated with, owning an e-bike (Jones et al., 2016; Philips et al., 2024), and at times found to be a hindrance (Wolf and Seebauer, 2014; Jones et al., 2024). There are few findings in the literature on the correlation between rurality and e-bike ownership. Our observation that in Germany, living in a city is negatively correlated with ownership, is therefore of increased interest.

Table 2 also reports our results for regressing public transport ticket ownership on the same sets of covariates. In the general model (3), the probability of owning a public transport ticket decreases with age. Table A9 shows that ticket ownership is very high among the youngest adults, but lowest among people aged 50 to 70. For older respondents, ticket ownership rates increase again. Having children in the household, owning a car, and a larger distance to the nearest public transport stop have significant negative correlations with ticket ownership. Being female and living in a city, rather than living in a village or in the countryside, have a positive correlation with ownership. This is also reflected in Table A13, which shows that the proportion of ticket owners is much higher in the city states of Berlin, Hamburg, and Bremen. Voting for the Green Party and a more negative perception of the consequences of climate change are also positively related to owning a ticket, while self-assessed environmentally conscious behavior does not seem relevant here. According to the model, education is also not significantly correlated with ticket ownership - although it is worth pointing out that in a simple t-test, the proportion of university degrees is significantly higher in the group of ticket owners (see Table A6).

In the commuters model specification (4), being employed has a strong negative association with ticket ownership and living in a town is now also positively related to ticket ownership. A larger distance to the workplace has a significant positive correlation with ticket ownership, while the distance to the nearest public transport station remains significant and negative, implying that commuters living closer to stops are more likely to own a ticket. Table A11, however, reveals that while people who live less than 1 km from their workplace are much less likely to own a ticket, living more than 25 km away from the workplace is again associated with slightly lower ticket ownership rates, suggesting a possible non-linear relation.

In comparison to e-bike ownership, it stands out that many associations with socioeconomic characteristics are reversed for ownership of public transport tickets. Respondents aged 50 to 70 years are least likely to own a ticket (see Table A9). This could be related to traveling less by car at a younger and at a higher age, whereas middle-aged individuals often use cars more intensively, such as for commuting or when having young children in their households. Also, students and retirees may have options of purchasing discounted tickets. Public transport ticket owners are less likely to own a car and are more likely to live in cities or larger towns than in villages or the countryside. This is not surprising as there is better infrastructure in urban areas. Being employed or self-employed is negatively correlated with ticket ownership in the commuters' model which only includes those employed and those currently in school or at university, which may seem unexpected, but is in line with Simma and Axhausen (2001) and can potentially be explained by a larger share of students and retired people using public transport rather than cars. Reasons for this may be that owning a car is more expensive than using a public transport ticket, and that (self-) employed individuals try to save time using cars rather than relying on potentially slow and inefficient public transport infrastructure. Overall, our findings largely align with the literature regarding correlations with being female (Simma and Axhausen, 2001; Giesel and Köhler, 2015; Busch-Geertsema et al., 2021), lower car ownership (Simma and Axhausen, 2001), higher education (Busch-Geertsema et al., 2021; Kersting et al., 2021), living in a city (Simma and Axhausen, 2001; Buehler, 2011), environmentally friendly attitudes (Hunecke et al., 2001; Matthies et al., 2002; Bamberg et al., 2007), and shorter distance to stops (Buehler, 2011). In contrast to some previous studies, we find a potentially non-linear association between ticket ownership and the distance to workplace, following an inversed u-shape (cf. Chng et al., 2016; Busch-Geertsema et al., 2021; Rasca and Saeed, 2022).

4.2. Latent Class Analyses

After identifying relevant individual characteristics associated with e-bike and ticket ownership, we are interested in finding distinct ownership groups for each transportation alternative. For this purpose, we conduct two latent class analyses (LCAs), one for the subsample of e-bike owners and one for the subsample of ticket owners. An LCA algorithmically splits a sample - in this case, the owners of an e-bike or of public transport tickets, respectively - into distinct groups, distinguished by the distributions of relevant, observable characteristics within these groups (Vermunt and Magidson, 2002; Weller et al., 2020; Haas et al., 2022). The closely related latent profile analysis (LPA) is used with characteristics that are based on continuous variables, while the LCA works for categorical variables, which are called items in this context. We use a combination of LCA and LPA since the set of observable characteristics that we include in this analysis contains both continuous and categorical variables. We use all variables included in the general model of the previous LPM analyses as the basis for our LCAs, since all were significantly correlated with at least one type of ownership. We do not include "Distance to workplace" since it is only relevant to the working subgroup of participants, and we do not include "Distance to public transport" since the variables "City" and "Town" (with reference level "Rural/Village") are expected to provide sufficient locational information.

We first determine the number of classes or user groups that best fit our data by using the Log-Likelihood as well as Akaike's and Bayesian information criteria to assess the goodness of fit (Vermunt and Magidson, 2002). A larger (that is, less negative) Log-Likelihood and smaller information criteria indicate better fits (Table A17). We check the fits for up to ten classes. For each number of classes, we also report the count of individuals in the smallest class and its relative class size. While fit indices advocate for more classes, we decided to set a limit at a minimum of 10% of the respective sample of owners to prevent identified classes from becoming excessively small. Trial analyses with more and smaller classes were run, but the additional classes obtained can be described as further splits of previously identified classes by additional characteristics (such as gender) that do not seem to provide much additional insights for interpretation. Following the 10% rule, we decide to go with 3 classes of e-bike owners and 6 classes of ticket owners (see Table A17).

We also ran LCAs on the subsamples of e-bike-non-owners and ticket-non-owners, with three groups, mirroring e-bike owner groups, and six groups, mirroring ticket owner groups, to compare them to our LCA results on owners. We numbered the Groups from N1-N3, and N1-N6, respectively (see Tables A18 and A19).

4.3. Results: LCA of E-Bike Owners

Tables 3 and 4 show the results of the LCAs for e-bike and ticket owners, respectively. Both tables contain the probabilities or expected means of the characteristics, the number of observations and their shares for each class. For ease of comparison, the variable means of all owners and all non-owners are also added to the right-hand side of the tables.

For e-bike owners, the largest of the three groups (Group 1) makes up 43% of all owners and consists of older (mean age of 70 years) and retired respondents (Table 3). Like the majority of e-bike owners, they usually have cars in addition to their e-bikes. E-bike owners in Group 2, which makes up 36% of all owners, are a bit younger, with an average age of 55 years, and almost all of them are working. Group 3 consists of the remaining 21% of e-bike owners and here respondents are distinctly younger, with 37 years on average, highly educated, mostly working and stand out by the, by far, highest probability across all e-bike owner groups of having children below 14 years in their households. They also show the highest probability of voting for the Green Party and perceive climate change consequences as particularly negative.

The three groups of **e-bike owners** assigned by the LCA can be summarized thusly:

- Group 1: Leaning older and retired
- Group 2: Leaning middle-aged and (self-)employed
- Group 3: Leaning younger with kids, higher educated, and green

Overall, e-bike owners usually have cars in addition to their e-bikes, with very high rates of car ownership, exceeding 90%. Further, about one quarter (24%) of e-bike owners in all groups live in large cities, which is less than the proportion of non-owners (35%). While this proportion is still substantial, it confirms that e-bikes are more popular in smaller towns and the countryside. Between these three groups of owners as identified by the LCA, though, there are no striking differences in their places of residence.

Comparing our resulting classes with those found for the Netherlands by Haas et al. (2022), we find some overlaps. Among their five classes, the largest class is, similar to ours, made up of older, retired users, described as "traditional e-bike users" (p. 831), and they found one additional group of retired

Table 3: Latent classes for e-bike owners

	Group 1	Group 2	Group 3	E-bike owners	Non-e-bike owners
	Probability/marginal mean (Std.E.)			Mean (Std.D.)	
Age	70.42	55.16	36.57	57.72	55.67
	(0.298)	(0.329)	(0.460)	(14.45)	(16.19)
Male (d)	0.58	0.55	0.54	0.56	0.53
	(0.019)	(0.021)	(0.029)	-	-
University degree (d)	0.20	0.21	0.40	0.24	0.27
	(0.016)	(0.018)	(0.028)	-	-
Income (eq)	4.63	5.13	4.56	4.80	4.57
	(0.070)	(0.078)	(0.100)	(1.69)	(1.84)
Working (d)	0.00	0.96	0.87	0.54	0.55
	(0.004)	(0.017)	(0.020)	-	-
Single household (d)	0.21	0.14	0.09	0.16	0.30
	(0.016)	(0.015)	(0.017)	-	-
Children (d)	0.00	0.05	0.60	0.15	0.16
	(0.003)	(0.012)	(0.029)	-	-
Car ownership (d)	0.94	0.98	0.94	0.95	0.89
	(0.009)	(0.007)	(0.014)	-	-
City (d)	0.20	0.22	0.26	0.24	0.35
	(0.017)	(0.018)	(0.026)	-	-
Town (d)	0.41	0.38	0.34	0.38	0.38
	(0.019)	(0.21)	(0.028)	-	-
Vote Green Party (d)	0.17	0.16	0.29	0.19	0.17
	(0.015)	(0.016)	(0.026)	-	-
Climate change conseq. (d)	0.64	0.64	0.80	0.67	0.67
	(0.019)	(0.021)	(0.024)	-	-
Self-assessed env. behavior	3.51	3.31	3.46	3.42	3.30
	(0.030)	(0.033)	(0.044)	(0.76)	(0.78)
Share (%)	42.81	36.39	20.80	25.14	74.86
Size (n)	673	572	327	1,572	4,681

Abbreviations: (d) for dichotomous variable and (eq) for equivalized

users, being mostly women. Our second group are middle-aged and employed, comparable to Haas et al. (2022)'s second group. Our third group, the younger individuals with children, are comparable to their fourth group. Their fifth and smallest group of young persons (students, and lower education) do not have an equivalent in our LCA.

Repeating our LCA for the sample of non-owners results in three groups rather similar groups (see Appendix Table A18). Group N1 is mostly retired, older persons, but with a larger proportion of women. Group N2 comprises the middle-aged and employed with a slightly higher likelihood of having children. Group N3 tends to be younger and more green-leaning than the other groups of non-owners. All three have a higher proportion of single households. Comparing the three groups directly to their "counterpart" in the e-bike owner groups (i.e. Group 1 to Group N1 etc.), both the proportion of voting Green and the self-assessed environmentally conscious behavior are lower in the non-owner groups. Nonetheless, the three e-bike owner groups and the three e-bike non-owner groups overall seem to form similar patterns in both sub-samples.

4.4. Results: LCA of Public Transport Ticket Owners

For public transport tickets, the largest group of owners (Group 1) comprises about 22% of respondents (Table 4). Similar to the largest group of e-bike owners, this group consists of older persons, with a mean age of 72.5 years, who are retired. They predominantly live in cities and towns and own cars in addition to their tickets. Group 2 of ticket owners makes up 19% of the subsample. Respondents in this group are middle-aged (with a mean of 51 years), mostly working and live almost exclusively in larger cities. Group 3 of ticket owners holds a share of 17% of the subsample. They are also retired and have a mean age of 72.2 years. Unlike the first group, they are mostly female and live in single-person households. They usually do not hold a university degree and have, on average, lower incomes. They are somewhat more likely to live in large cities and only about 27% of them own cars in addition to their tickets, making them the class with the distinctly lowest rate of car ownership among all ticket owner groups. Group 4 makes up 16% of ticket owners. They are also middle-aged (48 years on average), often hold university degrees, are working and have the highest average income of all groups. About 28% of them have younger children in their households, which is the second-highest proportion among all ticket owner groups, and twice the average among both owners and non-owners. They tend to live in smaller towns and villages and almost all respondents in this group own cars in addition to their tickets. Group 5 contains 14% of respondents, who are even younger (38 years on average), live exclusively in cities and are highly educated. They are the group with the highest probability (49%) among ticket holders of having young children in their households. They are further more likely to describe themselves as living environmentally friendly, perceive climate change as problematic, and often vote for the Green Party. However, 68% of the respondents in this group also own cars. Lastly, Group 6 makes up 13% of the subsample and its members are the youngest at only 26 years on average. They are more likely not to be currently (self-)employed and consequently earn the lowest average incomes. Respondents in this group are likely to be students. They also tend to live in cities and 61% of them own a car or have access to a car in their household.

In general, owners of public transport tickets tend to live in larger cities and are, on average, better educated than non-ticket owners. They are also slightly more likely to live in single-person households. Car ownership is overall lower for ticket owners than for non-owners, but varies strongly between the subgroups. While car ownership for members of Groups 1 and 4 is very high (both around 95%), it is lower but not uncommon among Groups 2, 5, and 6 (61 - 68%). Only those in Group 3 stand out with a much lower likelihood of owning a car (27%). Furthermore, as with the groups of e-bike owners, we see that the groups are separated predominantly by age (with two groups each comprising older, middle-aged, and younger participants) and then by location.

The six groups of **ticket owners** can be summarized thusly:

- Group 1: Leaning older and retired with car
- Group 2: Leaning middle-aged, (self-)employed, and urban
- Group 3: Leaning older, single, female, and retired, without a car
- Group 4: Leaning middle-aged, high-income, (self-)employed, and rural
- Group 5: Leaning younger, well-educated, urban, high-income, and green with kids
- Group 6: Leaning young, male, and not (yet) employed

As other LCA studies often focus on attitudes and psychological factors, the closest comparison is the study by Rafiq and McNally (2021), whose research, however, is specific to the United States. They ran their LCA for five groups, and found three groups of employed individuals differentiated by gender and age, as well as a group of single, older women and a group of non-white younger and older individuals doing non-work trips.

Repeating our LCA for the group of non-owners, the created groups differed markedly from the groups found for the ticket owners (Table A19). There is no group that approximates Group 3 of the ticket owners (i.e. retired persons that are majority female), the group that is the most likely to have kids (Group N3) lives overwhelmingly rural areas, which is not the case for the ticket owners group with children (Group 5). Group N6 has especially high incomes, higher than any among the ticket owners, and Group N4, with on average the youngest individuals, is much more likely to have a job than the youngest group of ticket owners (Group 6), but is also 6 years older on average. Our LCA on the ticket owners, therefore, did not simply find groups which it would find in the overall population, and this separation thus provides additional information about the subgroups of ticket owners specifically.

Table 4: Latent classes for ticket owners

	Group 1	Group 2	Group 3	Group 4	Group 5	Group 6	Ticket owners	Non-ticket owners
	Probability/marginal mean (Std.E.)						Mean (Std.D.)	
Age	72.48 (0.541)	51.11 (0.884)	72.20 (0.646)	48.26 (0.942)	38.37 (0.122)	26.18 (0.81)	53.68 (18.38)	56.81 (15.04)
Male (d)	0.55 (0.038)	0.49 (0.038)	0.21 (0.036)	0.53 (0.039)	0.49 (0.044)	0.60 (0.042)	0.48 -	0.55 -
University degree (d)	0.29 (0.031)	0.25 (0.040)	0.16 (0.029)	0.39 (0.040)	0.74 (0.048)	0.27 (0.042)	0.34 -	0.25 -
Income (eq)	4.90 (0.133)	4.78 (0.164)	3.64 (0.148)	5.11 (0.143)	4.98 (0.185)	3.21 (0.186)	4.49 (1.89)	4.66 (1.79)
Working (d)	0.01 (0.007)	0.91 (0.028)	0.00 (0.000)	0.97 (0.020)	0.96 (0.021)	0.32 (0.055)	0.50 -	0.56 -
Single household (d)	0.20 (0.044)	0.45 (0.042)	0.86 (0.041)	0.18 (0.032)	0.18 (0.041)	0.30 (0.043)	0.36 -	0.24 -
Children (d)	0.01 (0.005)	0.10 (0.030)	0.00 (0.000)	0.28 (0.037)	0.49 (0.051)	0.06 (0.022)	0.14 -	0.16 -
Car ownership (d)	0.96 (0.026)	0.68 (0.040)	0.27 (0.063)	0.94 (0.023)	0.68 (0.044)	0.61 (0.043)	0.70 -	0.95 -
City (d)	0.63 (0.034)	0.96 (0.040)	0.72 (0.038)	0.00 (0.000)	0.96 (0.026)	0.48 (0.046)	0.63 -	0.24 -
Town (d)	0.24 (0.030)	0.00 (0.000)	0.22 (0.034)	0.69 (0.049)	0.00 (0.000)	0.31 (0.043)	0.24 -	0.41 -
Vote Green Party (d)	0.16 (0.025)	0.15 (0.036)	0.21 (0.032)	0.29 (0.036)	0.54 (0.049)	0.28 (0.039)	0.26 -	0.15 -
Climate change conseq. (d)	0.64 (0.033)	0.67 (0.040)	0.75 (0.036)	0.77 (0.035)	0.94 (0.026)	0.82 (0.034)	0.75 -	0.65 -
Self-assessed env. behavior	3.40 (0.051)	3.19 (0.066)	3.63 (0.063)	3.33 (0.061)	3.74 (0.069)	3.43 (0.070)	3.34 (0.78)	3.31 (0.78)
Share (%)	21.54	18.62	16.91	16.10	13.90	12.93	19.57	80.43
Size (n)	265	229	208	198	171	159	1,230	5,055

Abbreviations: (d) for dichotomous variable and (eq) for equivalized

5. E-Bike or Ticket Ownership and Patterns of Car Use

In the second part of this paper, we aim to examine whether e-bike or public transport ticket ownership is associated with differences in car use. If ownership of either goes along with meaningfully different patterns of car use, then the respective mode of transport could be a target for supportive policy interventions to shift towards sustainable mobility choices and thereby help advance the mobility transition. However, it is also possible that owning e-bikes and tickets is merely associated with an expansion in total mobility behavior but does not replace car use. To get a robust picture of individual car use behavior, we collected four different measurements for this study. The first measure is the frequency of car use in the past seven days prior to answering the survey. The second measure is the distance traveled by car in the last seven days, measured in kilometers. The third measure is the number of kilometers driven by all cars in the respondent's household over the previous year. We asked about the use of up to three of the household's cars. These were added up and divided by the number of persons above 13 years of age in the household (number of household members minus number of children 13 and below).[3] As our fourth measure, we asked whether a car is the primary mode of transport to get to work, school or university.

Participants without cars in their households were also allowed to indicate how often and how far they have traveled with a car in the last seven days and if a car is their primary mode of transport for commuting. For the total distance traveled by the households' cars per year, non-owners were assigned

[3]For our survey, we only elicited the number of children below 14 years of age in a household. Our "number of adults" as an approximation will thus be referred to as such from here on.

a value of zero for their kilometers. The measurements of kilometers driven in the past seven days and in the past year by all cars of the household are winsorized at the top 5% level to reduce potential biases caused by outliers.

5.1. Descriptive Statistics of Car Use Among E-bike and Ticket Owners

Table 5 shows the arithmetic means and standard deviations of the four car use measures for e-bike owners and non-owners as well as public transport ticket owners and non-owners, respectively. At first glance, car use does not differ strongly between e-bike owners and non-owners. E-bike owners have only slightly lower numbers in three out of four measures, and a slightly higher number when it comes to their kilometers driven per year. Looking at public transport ticket owners versus non-owners, though, car usage is clearly lower in all four measures for owners. In the following, we investigate these differences - or the lack thereof - via ordinary least squares (OLS) and propensity score matching (PSM).

Table 5: Means (Std.D.) of car use measures across groups of e-bike owners

	E-Bike		Public transport ticket	
Car use measure	Owners	Non-owners	Owners	Non-owners
Car use frequency in past 7 days	7.70 (7.89)	7.66 (7.57)	3.88 (5.62)	8.59 (7.80)
Km driven by car in past 7 days	123.35 (145.08)	125.77 (137.02)	59.72 (105.21)	141.42 (146.51)
Km driven by car in past year	8,771 (5,956)	8,254 (6,992)	5,022 (5,691)	9,203 (6,731)
Use car to commute (d)	0.59 -	0.60 -	0.23 -	0.69 -
N	1,572	4,681	1,230	5,055

Note on variable "Use car to commute": (d) for dichotomous variable, "n/a" indicates that participants in this group do not (usually) commute as they are already retired.

A key concern is that differences in car use between non-owners and owners of either alternative cannot be unambiguously attributed to e-bike or ticket ownership as there could easily be differences in other individual characteristics, such as income or place of residence, which affect both the respective ownership and car use outcomes. It is unclear how those individuals who own an e-bike or a ticket would use (their) cars, if they did not own their e-bikes or tickets. Similarly, the car use patterns observed for each distinct group of e-bike or ticket owners, as identified by the LCAs, may not be due to the ownership but could just as likely be associated with other characteristics.

For instance, retired people may generally use their cars less, regardless of whether they own an e-bike. In other words, due to the lack of a random, exogenous allocation of the participants of the survey to ownership of e-bikes or tickets, there is no valid control group that models a counterfactual outcome. We therefore cannot interpret average differences in car use outcomes as causal effects of e-bike or ticket ownership. To nevertheless get a better picture of how car use behavior may be correlated with e-bike or ticket ownership, we run regressions that control for those covariates that were already found to be associated with ownership. We also use PSM to create a more comparable group as counterfactual to test for differences. It will show that both approaches lead to similar results, which all distinctly differ from a simple comparison of means.

5.2. Regression Analyses and PSM on Car Use

For all main regression analyses, we use our four different car use measures as dependent variables and run two different regression specifications with each for both transport alternatives. For the first model, we run OLS regressions with covariates. The second model shows results from a 1:1 PSM without replacement.[4]

The equation used for all model specifications is set up as follows:

$$caruse_{i,j} = \delta_0 + \delta_a \cdot A_i + \delta_z \cdot Z_i + \rho_i \tag{2}$$

where $caruse_{i,j}$ is a placeholder for one of the four car use measures (j) described above for the individual (i), A_i stands for either e-bike or ticket ownership, and Z_i includes additional covariates, if included in the respective model. Selected covariates are the same as previously used for the LCAs and they are also used for the calculation of the propensity scores. In the next paragraphs, we outline the rationale behind the PSM approach and the details of the selected matching procedures.

The PSM method estimates the propensity of being part of a group - in our case the ticket or e-bike owners, respectively - contingent on important characteristics (Rosenbaum and Rubin, 1983). Using this propensity score, one can then determine which individuals outside of this group of owners exhibit characteristics that are closest to those of the owners, and match them to the owners to achieve a better base for comparison. After matching and discarding the unused observations, propensity scores should ideally be distributed equally among owners and matched non-owners. In studies with a group that experienced a real "treatment" or intervention of some kind, PSM then allows for an estimation of the effect of this intervention. Since ownership of an e-bike or public transport ticket is not comparable to a treatment or intervention, we cannot speak of our results as "effects", but the PSM does help us with identifying correlations between ownership and car use more accurately. A PSM analysis reports its results in a similar manner to an OLS regression, with estimated coefficients that we report in the results of this section.

For our analysis, we calculate the propensity scores through logit regressions with ownership of the respective transport alternative as the dependent variable.[5] Generally, all variables relevant to ownership as well as variables that are expected to affect the outcome, which is car use in our case, should be included in the calculation of the propensity scores. However, no variables that may be affected by the group membership (i.e., ownership) should be considered. For this reason, we select for the calculation of our propensity scores the same variables previously identified as relevant to ownership of e-bike or public transport tickets, except for car ownership. After calculating the propensity scores, there are different approaches to matching, that is, to creating a group as counterfactual that is most comparable in their observable characteristics.[6] For our study, we focus on nearest neighbor (NN) matching methods, which are among the most common approaches (Harris and Horst, 2016). They match a specified number ”n” of individuals from the non-owners group to each individual of owners based on the most similar characteristics, that is, in the case of PSM, based on the most similar propensity score. Matching can be done without replacement, which means that once a non-owner individual has been matched with an owner they leave the pool of potential matches and cannot be paired again. This could lead to lower quality matches as subsequently only pairs who are not as similar to each other (that is, whose propensity scores are further apart) can be found (Caliendo and Kopeinig, 2008). In matching with replacement, on the other hand, non-owners can be matched repeatedly. This facilitates matching close pairs and decreases the variance of the estimated effect but can increase the bias as the comparison group is built of fewer unique observations (Heinrich et al., 2010; Li, 2013). For our study, we implement 1:1 matching without replacement and - relegated to the Appendix for brevity - 1:3 matching with replacement. Given

[4] Additional models are shown in the Appendix and include results from simple OLS regressions with the whole sample without matching or adjusting for covariates. This regression is equivalent to a simple two-sided t-test comparing means across owners and non-owners of e-bikes and tickets, respectively. We also show alternative matching approaches, that is, 1:3 matching with replacement and matching with additional adjustments for covariates in the already matched samples (Tables A20 and A21).

[5] Since not all respondents answered all survey questions, there are slightly different subsample sizes for each measure of car use. To account for this, we calculate a new set of propensity scores and apply the matching procedure to each subsample separately.

[6] A comparison group built by matching on observable variables may to a certain degree also indirectly adjust for the distribution of the unobserved variables if these are correlated with observed ones (Stuart, 2010).

that the pool of potential observations for comparison (non-owners) is at least three times as large as the group of owners for each transportation alternative, we do not expect difficulties in finding good quality matches for the majority of individuals in the owner groups. For all matching approaches, we nonetheless additionally make use of calipers, which restrict matching to pairs that are within a predefined range of closeness to each other, measured by the propensity scores. By doing so, bad quality matches are avoided at the cost of losing some observations that may be considered outliers (Caliendo and Kopeinig, 2008; Harris and Horst, 2016). The most efficient distance was found to be a caliper width of 0.2 to 0.25 of the standard deviation of the logit of the propensity score (Rosenbaum and Rubin, 1983; Austin, 2011b). We choose a caliper width of 0.25 for all matching approaches to avoid discarding too many observations that could not be matched with narrower calipers. After matching, we check whether samples are balanced by comparing the differences in covariates between owners and matched non-owners (Li, 2013). The quality of the match can be assessed by calculating the standardized mean bias, which should be below 10% for "good" matching results and which we report in the Appendix Tables A22 to A29 (Heinrich et al., 2010; Austin, 2011a; Stuart, 2010; Li, 2013). These tables also show that the matched subsamples are not significantly different from the owner subsamples in any of the included variables, while for the full sample, i.e., without any matching, there are significant differences in the distribution of many variables. A summarized measure as the average across all matching variables and across all four dependent variables is also reported as a single indicator per regression model in the respective result tables. Also, the distributions of propensity scores for owners and matched non-owners are shown for all models (Tables A30 and A31). Some additional matching methods were tested, such as 1:1 with replacement and different caliper sizes, but they resulted in inferior matching outcomes, either due to increases in the bias or substantial loss of observations. Those results are therefore not reported.

5.3. Model Results Regarding Car Use Patterns

Table 6 shows our results for regressing car use measures on e-bike or ticket ownership, complementarily using OLS with covariates, and 1:1 nearest neighbor matching without replacement (Stuart, 2010). Additional tables showing results of OLS without covariates (t-tests), 1:3 nearest neighbor matching with replacement, and a PSM model that simultaneously adjusts for covariates can be found in the Appendix Tables A20 and A21. The number of observations varies slightly depending on the number of responses to the different car use questions in the survey.

Table 6: PSM and OLS results for regressing car use on e-bike and ticket ownership

	E-bike ownership		Ticket ownership	
	OLS unmatched & covariates	NN[a] 1:1 without replacement	OLS unmatched & covariates	NN[a] 1:1 without replacement
Dependent variable	Ownership coefficient (Std.E.)			
Car use frequency in past 7 days	-0.560** (0.234)	-0.644** (0.298)	-3.293*** (0.267)	-3.180*** (0.298)
Km driven by car in past 7 days	-16.276*** (4.444)	-20.444** (5.699)	-51.655*** (5.078)	-54.756*** (5.832)
Km driven by car in past year	57.386 (203.125)	-45.383 (250.028)	-2778.142*** (231.326)	-2831.697*** (287.420)
Use car to commute (d)	-0.056*** (0.020)	-0.060** (0.025)	-0.358*** (0.022)	-0.359*** (0.028)
N (treated)[b]	1,341	1,341	1,041	984
N (control)[b]	3,911	1,341	4,232	984
Avg. mean bias[c]	11.0	1.3	26.7	2.1

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
a: NN = Nearest Neighbor Matching
b: N refers to the number of participants who answered the question for "car use frequency in past 7 days". The N for dependent variables vary slightly. Exact counts listed in Tables A22 to A29 in the Appendix.
c: Average of the standardized mean bias across all four dependent variables shown in percent
(d) for dichotomous variable

Running OLS without covariates with only the ownership dummy as an explanatory variable corresponds to a t-test between owners and non-owners. The unmatched OLS results (Table A20) imply that, not taking into account any other factors, there is no statistically significant difference in car usage between e-bike owners and non-owners, except in the total amount of kilometers driven per year. For ticket ownership, though, the difference is significant, even in the simple comparison of means (Table A21).

However, he two groups are not directly comparable as they exhibit differences in many characteristics, some of which influence both car usage and e-bike ownership. Therefore, we consider the results of those of our models employing covariates (Table 6) to paint a much more informative picture of how e-bike owners and non-owners differ in their car usage, while still refraining from conclusions about causality.

E-bike ownership seems to be statistically significantly correlated with lower car use in all outcome measures except the total kilometers per year. Notably, the coefficients of the OLS regression with covariates and the PSM model are in general rather similar to each other. Car use frequency in the past seven days is 0.56 and, respectively, 0.64 trips lower, the number of kilometers driven by car in the last 7 days is 16.3 and, respectively, 20.4 kilometers lower, and the likelihood that the car is used as main mode to commute is 5.6 and, respectively, 6.0 percentage points lower. For kilometers driven by car in the past year per adult in the household as the outcome variable, the correlations with e-bike ownership are not statistically significant. Considering that the survey was conducted in springtime, this may be due to seasonality as e-bike owners might be using their bikes more often in good weather, but possibly prefer to mainly use their cars in winter, contributing to more kilometers driven yearly while having lower numbers for the last seven days.

While the literature frequently reports e-bikes replacing car use especially for commuting (Sun et al., 2020; Söderberg et al., 2021; Haas et al., 2022) and being linked to lower car ownership (Sun et al., 2024), our results indicate a more moderate correlation between e-bike ownership and lower car usage, with our coefficients below the median mode substitution rate of 24% reported by Bigazzi and Wong (2020). While Haas et al. (2022) report for the Netherlands that the group of e-bike users who use their bike for commuting increases faster than the group of leisure users, this shift may not be noticeable in Germany. While there are statistically significant correlations between a lower likelihood of commuting by car and e-bike ownership in our sample, the magnitudes are small.

Ticket ownership statistically significantly corresponds to visibly lower car usage in both models and with all outcome measures. Car use frequency in the past seven days is 3.3 and, respectively, 3.2 trips lower, the number of kilometers driven by car in the last 7 days is 51.7 and, respectively, 54.8 kilometers lower, and public transport ticket owners drive 2,778 and, respectively, 2,832 kilometers less per year than non-owners. All of these coefficients are much larger than those in the models concerning e-bike ownership. The likelihood that the car is used as the main mode to commute is about 36 percentage points lower, a correlation which is an entire order of magnitude larger than that between e-bike ownership and car commuting. These strong correlations corroborate findings from previous studies, which report public transport being linked to lower car use (Jou and Chen, 2014; Şimşekoğlu and Klöckner, 2019; Schaefer et al., 2021).

A full version of all car use OLS regressions with covariates can be found in the Appendix (Tables A32 and A33) and also presents some additional information on other factors relevant to car use.

5.3.1. Car Use Patterns of LCA Groups of E-bike Owners

To look at the groups of e-bike owners as found by the LCA in more detail, we ran matching analyses for each group separately (Table 7). While for the group of e-bike owners as a whole, we have found ownership to be significantly correlated with three out of four car measures, this is not the case when looking at the groups separately. For Group 1, with predominantly older and retired persons, e-bike ownership correlates with about 600 kilometers more that were driven per person in the household in the past year. Since in the PSM, this group was matched with people in the same age range who do not have an e-bike, this correlation makes sense. An older person who is still active and mobile enough to own and possibly operate an e-bike is likely to be more mobile in regards to other transport modes as well, including driving. Group 2, on the other hand, including middle-aged and employed participants, shows a negative correlation between e-bike ownership and the number of kilometers driven in the past 7 days, as well as the likelihood of using a car for their commute. Here, the e-bike may very likely be used as an occasional replacement for the car. Group 3, however, leaning towards comprising young families, does not show any significant correlations between owning an e-bike and their car usage.

Table 7: PSM results by LCA group - e-bike ownership coefficients

	LCA groups ebike owners		
	Group 1	Group 2	Group 3
Correlation of e-bike ownership with:	Coeff. (St.E.)	Coeff. (St.E.)	Coeff. (St.E.)
Car use frequency in past 7 days	-0.586	-0.474	-0.854
	(0.361)	(0.536)	(0.689)
Km driven by car in past 7 days	-2.739	-21.379**	-18.139
	(6.782)	(10.310)	(12.479)
Km driven by car in past year	582.560**	-5.053	-341.135
	(279.798)	(471.192)	(586.685)
Use car to commute (d)	.	-0.062**	-0.039
	.	(0.031)	(0.042)
N (owners)^a	568	477	295
N (control)^a	568	477	295
Avg. mean bias^b	1.86	3.73	4.97
Group leans:	- Older - Retired	- Middle-aged - (Self-)employed	- Younger - With kids - Green

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
All models: Nearest Neighbor 1:1 matching without replacement
a: N of model with 'Car use freq. in past 7 days', N for dependent variables varies slightly.
b: Avg. of standard. mean bias across the models of all four dep. variables

5.3.2. Car Use Patterns of LCA Groups of Ticket Owners

As with the LCA groups of e-bike owners, we also ran PSM analyses for all LCA groups of public transport ticket owners (Table 8). Correlations between ticket ownership and almost all car use measures are significant and negative. Lower car use frequency as well as a lower number of kilometers driven in the past 7 days is most strongly correlated with ticket ownership for Group 2 - those respondents who tend to be middle-aged and live in cities. Lower kilometers driven in the past year overall and lower likelihood to be using the car for commuting were most strongly correlated with ticket ownership for participants from Group 6 - this makes sense, since this is the group hypothesized to consist of younger students. Overall, coefficient magnitudes are in a similar range as in the models summarized in Table A21.

5.3.3. Car Use Patterns for Owners of both E-Bike and Public Transport Ticket (Interaction)

Finally, we also investigate if owning both an e-bike and a public transport ticket has any effects that differ from each single correlation between the respective mean of transport and car use. We do so by adding an interaction term for owning both to the OLS regressions on car use, including also covariates

Table 8: PSM results by LCA group - ticket ownership coefficients

	LCA groups ticket owners					
	Group 1	Group 2	Group 3	Group 4	Group 5	Group 6
Correlation of ticket ownership with:	Coeff. (St.E.)	Coeff. (St.E.)	Coeff. (St.E.)	Coeff. (St.E.)	Coeff. (St.E.)	Coeff. (St.E.)
Car use frequency in past 7 days	-1.378** 0.576	-5.426*** 0.644	-3.147*** 0.483	-2.714*** 0.902	-3.782*** 0.623	-3.241*** 0.920
Km driven by car in past 7 days	-25.939*** 9.928	-78.669*** 14.241	-44.319*** 8.967	-52.490*** 17.900	-77.156*** 15.499	-47.644** 20.679
Km driven by car in past year	-70.345 392.767	-4138.465*** 769.884	-3393.545*** 504.279	-2829.605*** 713.878	-3408.086*** 754.145	-4548.307*** 1247.052
Use car to commute (d)	. .	-0.438*** 0.048	. .	-0.309*** 0.052	-0.312*** 0.050	-0.500*** 0.078
N (owners)^a	222	188	143	168	147	79
N (control)^a	222	188	143	168	147	79
Avg. mean bias^b	2.78	4.80	2.77	5.01	4.28	7.93
Group leans:	- Retired - With car	- Middle-aged - (Self-) employed - Urban	- Retired - Female - Single HH - No car	- Middle-aged - High income - (Self-) employed - Rural	- Younger - High income - Green - Urban - With kids	- Young - Male - Not (yet) employed

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
All models: Nearest Neighbor 1:1 matching without replacement
a: N of model with 'Car use freq. in past 7 days', N for dependent variables varies slightly.
b: Avg. of standard. mean bias across the models of all four dep. variables

as before (Table A34). In our sample, 238 individuals, that is 3.8%, own both an e-bike and a public transport ticket. While we observe no significant association between owning both and the frequency of car use in the past seven days, there are positive and significant coefficients for the regression models using the kilometers driven in the past 7 days and over the whole year as well as the likelihood to take the car for the daily commute as the dependent variables. Simultaneously, the coefficients indicating the separate associations between e-bike ownership as well as ticket ownership with all car use outcomes remain almost unchanged in terms of significance and magnitude as compared to the models that include only either e-bike or ticket ownership as the central explanatory variable of interest suggesting little interaction between the two transport alternatives. Importantly, the sums of the negative coefficients for e-bike and ticket ownership and the positive coefficient of the interaction term are smaller than zero across all models, revealing that the net sizes of the associations of owning an e-bike and a ticket with car use are still clearly negative, and only diminished by the additional effects of owning both. This seems intuitive as an individual owning both an e-bike and a ticket can most probably not replace as many trips by car with each alternative as someone with only one of these alternatives can. For more information on those who own both transport alternatives simultaneously, see Table A7.

6. Conclusions

We used data from a representative 2022 survey among Germans to characterize e-bike and public transport ticket owners and their respective car use patterns. Our approach comprised linear probability models (LPM) to identify relevant characteristics, latent class analyses (LCAs) to identify distinct user groups, and further OLS regressions as well as propensity score matching (PSM) approaches to discern differences in car use between owners and non-owners of e-bikes and public transport tickets, respectively. According to our findings, owner groups for e-bikes and public transport tickets are distinctly different from one another and there is only a small overlap (4% in total) who have access to both alternatives.

Overall, our results on characteristics of e-bike owners largely align with those found by previous studies

(Wolf and Seebauer, 2014; Şimşekoğlu and Klöckner, 2019; Sun et al., 2020; Jones et al., 2024; Philips et al., 2024; Ren et al., 2024; Poier et al., 2025). We find that owners of e-bikes are on average older, have higher incomes, live less often in cities, live slightly closer to work, and commonly own cars in addition to their e-bikes. The LCA identified three typical groups of e-bike owners, the largest of which consisted of retirees.

Ticket owners are more likely to live in cities, are, on average, younger, better educated, and are less likely to own cars, correlations which corroborate previous studies (Simma and Axhausen, 2001; Matthies et al., 2002; Bamberg et al., 2007; Buehler, 2011; Kersting et al., 2021; Giesel and Köhler, 2015; Busch-Geertsema et al., 2021). An LCA produced six distinct groups of ticket owners, characterized by their differences in age, employment status, place of residence, income, and family status. Most of these groups showed a substantially lower rate of car ownership as compared to non-owners.

In the second part of our paper, we look at the correlations between e-bike and ticket ownership with four different car use measures: car use frequency in the last seven days, kilometers driven in the past seven days, total kilometers driven in the past year, and whether the car is the respondent's main mode of commuting.

E-bike owners' car use was statistically significantly lower in all measures except the kilometers per year, but magnitudes were moderate, with about 0.6 fewer trips by car per week, 16 to 20 fewer weekly kilometers by car, and being around 6 percentage points less likely to commute by car. Since the vast majority of the e-bike owners in our sample also have access to at least one car in their household, our results suggest a complementary relationship between e-bikes and car use, where both transport modes are present in the household and serve different purposes.

Magnitudes are larger for the group of ticket owners, with about 3.2 fewer trips by car per week, 52 to 55 fewer weekly kilometers, and being about 36 percentage points less likely to commute by car. Total kilometers driven per year were around 2,800 less than for non-owners.

However, whether these findings indicate that e-bike and ticket owners are behaviorally distinct groups due to preexisting mobility preferences or whether they indicate a causal effect of e-bike and ticket ownership on car use cannot be discerned by this descriptive study and requires further research. Also, our approach of PSM can only take into account observed (and observable) characteristics. There may be relevant factors that we have not considered, such as physical limitations that prevent individuals from using e-bikes, tickets or cars. There may also be an unobservable individual preference for car ownership and use that is not reflected in any of the collected variables other than car ownership and car use outcomes themselves. Eventually, future studies could also implement an external, randomly allocated provisioning of sustainable transport alternatives, ideally over a longer period of time, to produce more insightful results on the causal effects on car use.

In addition to the data that our survey provides, it would be interesting to ask respondents about their motivations for (not) purchasing e-bikes and tickets. Similarly, focusing on ownership, our study could not go into detail about how e-bikes and tickets are used due to data limitations. There are certainly interesting behavioral research questions regarding e-bike and public transport use – how often are they used and at what times, for which trips? How often do we observe multimodal behavior, where ownership of one makes the usage of the other more likely? These are promising questions for further studies which elicit more detailed behavioral data. LCA that includes behavioral details may show a different and relevant dimension of e-bike or ticket owners and their subgroups.

Modal shift promoting policies aim at motivating owners of e-bikes and tickets to use their modes more intensively in place of cars. Yet, the prerequisite for usage is access to the mode, either by owning the vehicle or by having access through, for example, public transport tickets. Therefore, to change mobility behavior effectively, it is vital to consider both the roles of ownership as well as of usage behavior. With our study, we focused on patterns of ownership and their associations with car use.

For e-bike owners, we see that they predominantly commute by car (LCA Groups 2 and 3). Here, one aim could be to motivate more owners to use their bikes for commuting as well as for obligatory trips like grocery shopping. E-bike usage for those trips has been increasing in the Netherlands (Haas et al., 2022) and would likely require infrastructure investment for better and safer bike lanes as well as good connectivity to public transport, especially in more rural regions. Intermodal connectivity will also require charging and safe storage options for e-bikes at public places like train stations and shopping areas.

Policymakers may also focus on winning new users. For example, persons in cities may be more likely to live in apartment buildings without charging and safe storage options. Purchases and subsequent usage of e-bikes in urban areas may hence be promoted through respective infrastructure, in addition to traffic infrastructure that makes riding in cities safer. As our results show that people who earn lower incomes are currently not well-represented among e-bike owners, monetary incentives, such as subsidies, may motivate purchases also among additional socioeconomic groups. Some of these barriers that seem particularly specific to urban areas may also be overcome by expanding affordable e-bike renting and sharing options. Overall, the observed complementarity between e-bike and car ownership shows that e-bikes are unlikely to replace all car trips for their owners, which should be considered in policymaking.

For owners of public transport tickets, the strong correlations to lower car use show that they already use public transport for a large range of trips, including commuting. Therefore, for the city-dwelling members of these groups, it seems most important to maintain connectivity, have adequate frequency of buses and trains to support their needs, and ensure general safety. Improvements made to existing networks can still center specific groups. For example, for the groups of older ticket owners, as identified by our analysis, ensuring the safety and ease of entering at stops is likely vital for them to continue using their ticket. Since public transport ticket owners tend to earn lower incomes on average, keeping tickets affordable, as through the *DeutschlandTicket* is also vital.

To retain more remotely-living users as well as to reach respective new user groups, accessibility and speed of connections are vital (Boulange et al., 2017; Ding et al., 2017). To attract new people to public transport in rural regions, larger infrastructure projects may be needed, which could make traveling by public transport not only a sustainable but also a fast, cheap and convenient alternative to driving.

Overall, we suggest that policymakers look at a respective region's socioeconomic distributions and then use studies such as ours – or other detailed accounts of ownership patterns – to discern current groups of owners, or conversely, deduce which might be promising future owners and users. Our LCA groups can be informative here, both by showing which groups may exist, and also how these groups may be using their ticket or e-bike, through their correlations with higher or lower car usage. With our study, we have identified a number of important characteristics that may help target supportive measures to specific groups of people to make the most efficient use of public funds and policy momentum, and effectively further the transition to more sustainable transport modes.

❖

A. Appendix

This paper's supplementary materials can be found online and downloaded as pdf here:

https://www.rwi-essen.de/fileadmin/user_upload/RWI/Publikationen/Anhang/Supplementary_Materials_Electric_Bicycles_and_Public_Transport_Tickets_Ownership_and_Car_Use_Patterns.pdf

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