Transport Policy 162 (2025) 242–259

Contents lists available at ScienceDirect

Transport Policy

journal homepage: www.elsevier.com/locate/tranpol

Electrifying: What factors drive the transition toward electric vehicle adoption in the Netherlands?

Linlin Zhang *, Dea van Lierop, Dick Ettema

Department of Human Geography and Spatial Planning, Faculty of Geosciences, Utrecht University, Utrecht 3584 CB, the Netherlands

ARTICLE INFO

Keywords:
Electric vehicle (EV)
Household fleet composition
Transition
Ownership
Leasing

ABSTRACT

This study examines car adoption in the context of household car fleet choices using data from the Dutch National Travel Survey (2018–2020) and nested logit regression models. We analyze the factors associated with the selection of different vehicle types, including internal combustion engine vehicles (ICEVs), hybrid electric vehicles (HEVs), plug-in hybrid electric vehicles (PHEVs), and battery electric vehicles (BEVs), across one- and two-car fleets. Descriptive analysis indicates that BEVs and PHEVs are more prevalent in two-car households than in one-car households, where they are less likely to be the sole vehicle. Additionally, these vehicles are predominantly leased or company cars rather than privately owned, regardless of household fleet size. Model findings reveal that higher income strongly correlates with BEV and PHEV adoption, particularly for PHEVs in one-car households. Education also plays a significant role: one-car households adopting BEVs or PHEVs typically have higher education levels, with this effect being most pronounced for BEVs. Geographically, BEV adoption in one-car households is largely an urban phenomenon. Over time, the profile of BEV and PHEV adopters in two-car households has shifted. Dependence on higher education and urban concentration has decreased, reflecting a broader adoption pattern. These findings underscore the need for policies that address disparities in the uptake of electric vehicles, especially among user groups that are slower to adopt new technologies.

1. Introduction

In 2021, the transportation sector accounted for 37% of all energy-related CO_2 emissions globally, with private vehicles contributing approximately half of the sector's energy use and emissions (IEA, 2022b). The shift from internal combustion engine vehicles (ICEVs) to electric vehicles (EVs) is crucial for decarbonizing the transportation sector (Cano et al., 2018). However, despite this necessity, battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs) made up only 8.5% of global car sales in 2021 (IEA, 2022a), reflecting a slower-than-anticipated adoption rate. In this context, understanding households' decisions regarding car acquisition, particularly with respect to different types of EVs as part of the household car fleet, is vital for sustaining and accelerating this transition.

Insights into household decisions regarding vehicle ownership are grounded in separate bodies of literature on household car fleet choice and EV adoption. Studies on household car fleet size and composition have traditionally focused on ICEVs (Anowar et al., 2014a; Khan and Habib, 2021; Oakil et al., 2013; Rith et al., 2019). While these studies provide valuable insights, they often fall short when applied to the ongoing transition toward EVs. Research on EV adoption, on the other hand, frequently treats EVs as a uniform category, overlooking critical differences among hybrid electric vehicles (HEVs), PHEVs, and BEVs (Brückmann et al., 2021; Mandys, 2021; Tal et al., 2013). This oversight matters as each EV type presents unique characteristics, such as range limitations and reliance on charging infrastructure (Lane et al., 2018), which are likely to shape household decisions differently. By exploring the specific factors driving the adoption of each EV type, this study provides a more nuanced understanding of household decisions regarding car ownership during the EV transition. Recognizing these differences is essential for addressing the challenges and opportunities that arise as households integrate different EVs into their fleets.

Household car fleet size and composition play a role in EV adoption decisions. A household may choose to adopt an EV as its sole vehicle or as part of a larger fleet. Evidence suggests that BEVs are often used to complement ICEVs within households, as this arrangement requires less adaptation compared to households that rely exclusively on a BEV (Jakobsson et al., 2016; Pierre et al., 2011). Despite these insights, the

* Corresponding author.
E-mail addresses: l.zhang5@uu.nl (L. Zhang), d.s.vanlierop@uu.nl (D. van Lierop), d.f.ettema@uu.nl (D. Ettema).

https://doi.org/10.1016/j.tranpol.2024.08.002
Received 7 May 2023; Received in revised form 27 June 2024; Accepted 6 August 2024
Available online 8 August 2024

difference in EV adoption among households with different car fleets remains unclear. Therefore, this study examines how household fleet characteristics affect the adoption of EVs.

Furthermore, the transition to EV adoption is a dynamic process, explained by the diffusion of innovation theory (Rogers, 2003). In recent years, EV market share has grown significantly. Norway exemplifies this trend, with BEVs and PHEVs together accounting for 29.1% of new car sales in 2016, soaring to 74.7% in 2020. This rapid expansion has been accompanied by notable shifts in the demographics of EV adopters, as the market expands beyond early adopters to include a broader and more diverse population (Jenn et al., 2020; Lee et al., 2019). As new adopters emerge, the factors that drive or hinder EV adoption evolve, reflecting changes in the societal context and adopter characteristics. Understanding these shifts is essential for promoting inclusivity and sustaining the transition to EVs. However, limited research has explored these trends. This paper fills this gap by examining the evolving patterns of EV adoption and identifying the shifting drivers and barriers as the market progresses from niche adoption to broader mainstream acceptance.

This study aims to investigate the adoption of different types of EVs in relation to household car fleet choices and the factors that shape these decisions. We examine how household car fleet characteristics shape the decision to adopt EVs by comparing households with EVs to those with only ICEVs. We also distinguish between single-car and two-car households to identify differences in the motivation behind EV adoption. A key focus is to determine whether the factors driving EV adoption differ when an EV serves as the sole vehicle in a household versus being part of a larger fleet. Additionally, this study examines how adoption patterns and influencing factors evolved, using comprehensive data from the 2018–2020 Dutch National Travel Survey. This timeframe coincides with a period of rapid EV market growth in the Netherlands, offering valuable context for understanding the dynamics of household EV adoption.

2. Literature review

2.1. Household car fleet choice

Studies on household car fleet choices typically examine the number and types of vehicles, with a primary focus on ICEVs. Previous research suggests that fleet composition is influenced by various socioeconomic, demographic, and built environment factors. For example, larger households with more family members and licensed drivers are more likely to own multiple cars (Anowar et al., 2014b; Bansal et al., 2018). Additionally, households that are older, well-educated, and have higher incomes often own more vehicles (Rith et al., 2019). Larger vehicles with more seating and luggage space are more commonly chosen as household size and the number of children increases (Chen et al., 2020; Eluru et al., 2010). Younger individuals, the elderly, and employed individuals are more likely to be primary drivers of smaller vehicles (Chen et al., 2020). In North America, higher-income households tend to acquire sport utility vehicles (SUVs), coupe-type vehicles (Eluru et al., 2010), and other larger vehicles such as pickup trucks and vans (Chen et al., 2020). Moreover, those with higher income and education levels are more inclined to purchase fuel-efficient vehicles, including hybrid and plug-in hybrid models (Timmons and Perumal, 2016).

Regarding built environment attributes, transit accessibility and the population density of residential locations are key factors influencing household fleet size and composition. In North American cities, enhanced transit accessibility and higher residential density are associated with the acquisition of compact and smaller vehicles rather than larger pickup trucks, SUVs, and vans (Chen et al., 2020; Eluru et al., 2010), and with a reduced likelihood of car ownership overall (Anowar et al., 2014a; Khan and Habib, 2021). In the Philippines, greater access to facilities such as hospitals, markets, schools, and recreational centers reduces private car dependency and ownership (Rith et al., 2019). Additionally, larger vehicles like vans and SUVs are more commonly owned and driven by households residing in peripheral areas of North American cities (Anowar et al., 2015; Garikapati et al., 2014).

While existing studies have extensively explored household car fleet choices with a focus on ICEVs, the introduction of different types of EVs into household car fleets in the context of the transition toward electric transportation has received limited attention.

2.2. EV adoption

Existing research indicates that EV adoption is influenced by socio-economic and demographic characteristics, as well as built environment attributes. These influences have been explored using both preference (RP) data (Brückmann et al., 2021; Mukherjee and Ryan, 2020; Peters and Dütschke, 2014; Tal et al., 2013; Vassileva and Campillo, 2017) and stated preference (SP) data (Koetse and Hoen, 2014; Mandys, 2021; Plötz et al., 2014).

Males are more likely to adopt EVs compared to females (Peters and Dütschke, 2014; Vassileva and Campillo, 2017). Middle-aged individuals have a higher probability of owning an EV compared to the general population (Peters and Dütschke, 2014; Plötz et al., 2014). Individuals with higher education levels (Mandys, 2021; Mukherjee and Ryan, 2020; Vassileva and Campillo, 2017) and those with higher-incomes are more inclined to adopt EVs (Brückmann et al., 2021; Gehrke and Reardon, 2021; Mandys, 2021; Qorbani et al., 2024; Tal et al., 2013; Vassileva and Campillo, 2017; Yang et al., 2023). Larger families (Mandys, 2021; Peters and Dütschke, 2014; Plötz et al., 2014), and those living in single-family homes are more likely to be EV owners (Brückmann et al., 2021; Gehrke and Reardon, 2021; Tal et al., 2013). Additionally, individuals with lower annual driving mileage are more likely to become early adopters of BEVs, as they can more easily adapt to the limited driving range and long recharging times (Koetse and Hoen, 2014). In contrast, Mukherjee and Ryan (2020) observed that long-distance commuters who travel at least an hour a day are more inclined to adopt BEVs.

The geographic context significantly influences EV adoption decisions, but there is ongoing debate about where EVs are most suitable. The prevailing notion has been that EVs are better suited for urban areas than for suburban and rural areas (Ioannides and Wall-Reinius, 2015). This is partly due to the availability of charging stations, which play a crucial role in the early adoption of EVs (Almeida Neves et al., 2019; Canepa et al., 2019; Gehrke and Reardon, 2021; Mukherjee and Ryan, 2020; Yang et al., 2023). For instance, Gehrke and Reardon (2021) found that in Massachusetts, USA, EV charging infrastructure is generally first installed in urban areas, resulting in a higher density of charging points compared to rural areas. Similarly, Mukherjee and Ryan (2020) observed in Ireland that BEV adopters typically live near charging stations and tend to cluster around major urban centers. Additionally, Newman et al. (2014) suggested that the density of cities makes short trips by EV more practical, while the limited range and speed of EVs discourage rural residents from adopting them.

In contrast, some studies suggest that people living in low-density areas, such as suburban and rural regions, are more likely to own plug-in electric vehicles (PEVs) in the UK (Morton et al., 2018) and Norway (Hjorthol, 2013), where PHEVs and BEVs are grouped as PEVs. In Germany, potential first-time PEV adopters are identified as commuters living in suburbs with regular high-mileage driving patterns (Plötz et al., 2014). Households in suburban and rural areas rely heavily on cars due to limited public transportation options, making them more likely to benefit from the lower operating costs of EVs, especially with longer driving distances and more frequent car use (Fornahl and Wernern, 2015; Kitamura et al., 1997). Additionally, these households often have the space to install home charging points, as they typically reside in detached or semi-detached houses with gardens and garages (Kester et al., 2020).

While existing studies provide valuable insights into the determinants of EV adoption, most treat EVs as a single category without differentiating between HEVs, PHEVs and BEVs (Canepa et al., 2019; Kester et al., 2020; Lane et al., 2018; Mandys, 2021; Plötz et al., 2014; Wang et al., 2018; Wolbertus & van den Hoed, 2020; Zhuge and Shao, 2019). The few studies that differentiate between EV types typically focus on just one (Brückmann et al., 2021; Mukherjee and Ryan, 2020; Vassileva and Campillo, 2017). Investigating adoption decisions across different EV types requires a nuanced approach. People may have varying preferences for different types of EVs based on factors such as differences in technical limitations (Lane et al., 2018), environmental friendliness (Wang et al., 2018; Zhuge and Shao, 2019), and economic benefits like lower operating costs (Papaioannou et al., 2020). For instance, technical limitations, including limited driving range, long recharge times, and reliance on charging opportunities, remain significant barriers to widespread adoption (Mandys, 2021; Olson, 2018). As levels of electrification increase across HEVs, PHEVs, and BEVs, so do the challenges related to range limitations and charging infrastructure. These challenges are likely to influence adoption decisions for each type of vehicle differently. Moreover, these technical deficiencies, along with relatively high purchase costs, explain why many people still choose ICEVs over EVs. Therefore, to fully understand the transition to electric transportation, it is essential to differentiate between HEVs, PHEVs, and BEVs (Almeida Neves et al., 2019).

Household car fleet characteristics, including size and composition, also influence EV adoption. EVs are more likely to be adopted by multi-vehicle households than by single-vehicle households (Figenbaum, 2020; Peters and Dütschke, 2014). In most cases, EVs complement conventional vehicles within the household (Pierre et al., 2011). Specifically, for BEVs, adoption as a second car is better suited to multi-car households, as it requires less adaptation compared to using a BEV as the primary car in multi-car households or as the sole vehicle in single-car households (Jakobsson et al., 2016). However, potential differences in adoption patterns among households with different car fleets remain underexplored. For instance, the likelihood of BEV adoption may differ between one- and two-car households.

2.3. Changes in the EV landscape

Previous studies on EV adoption have primarily focused on early adopters, examining their characteristics in detail. As the EV market continues to expand, new user groups are likely to emerge, in line with innovation diffusion theory (Rogers, 2003). This suggests that current EV adopters may differ from earlier ones, making it important to capture the evolving trends and associated determinants. Few studies have identified these shifts. Lee et al. (2019) found that high-income families may not remain the largest group of PEV adopters as the market grows, with middle-to-high-income and middle-income households likely to adopt PEVs in increasing numbers. Similarly, Jenn et al. (2020) indicated that the PEV market is expanding beyond innovators and early adopters to include mass-market consumers with moderate incomes.

In terms of the built environment, Kester et al. (2020) used 2016 RP data to show that while early PEV adoption occurred mainly in urban and suburban areas in Nordic countries, rural usage has been on the rise. Initially, public charging stations were concentrated in urban areas, but the number of both public and private charging stations in suburban and rural areas has steadily increased. Additionally, more fast-charging stations are being installed along highways, and smart charging technologies—such as fast-charging and vehicle-to-grid (V2G)—are emerging. As a result, the spatial distribution of charging infrastructure is becoming more balanced, reducing disparities in access to charging and improving EV accessibility across different regions.

In addition, policies and incentives have played a key role in promoting EV adoption. For instance, the Netherlands has implemented subsidies for BEVs and extensively developed charging infrastructure (IenW, 2020). Moreover, technological advancements, such as improved battery life, extended driving range, and smart charging technologies, alongside expanded charging opportunities, can help alleviate range anxiety, thus boosting PEV sales, particularly for BEVs (Ashkrof et al., 2020). As the transition to electric transportation continues, it is essential to examine the adoption of different EV types across different population segments to ensure inclusivity and sustain momentum. However, most previous studies rely on cross-sectional data, limiting their ability to capture changes over time. Our study addresses this limitation by comparing data from two time periods to capture evolving adoption patterns and the nuanced changes in factors associated with the adoption of different EV types.

Taken together, while existing literature has broadly explored EV adoption, it has largely overlooked the role of household car fleet choices and the distinctions between different EV types. This study addresses these gaps by examining the adoption patterns of EV-using households and associated factors, differentiating between various EV types and household fleet compositions. Additionally, we investigate evolving trends in EV adoption, capturing differences between early and later EV adopters by analyzing data from two recent periods. Combining these elements in one study could provide a comprehensive view of EV adoption patterns and trends, as well as the factors shaping EV adoption.

3. Data and methods

3.1. Study context

According to the Dutch Climate Treaty and the government's electric transportation strategy, by 2030, all new cars sales in the Netherlands must be zero-emission vehicles, including those powered by batteries, hydrogen, and solar cells. To support this transition, approximately 1.8 million public charging stations will be available by that time (IenW, 2020). These efforts will significantly contribute to increasing the market share and diffusion of BEVs. Notably, PEV sales as a percentage of all new car sales in the Netherlands surged from 9.6% in 2015 to 33% in 2022, with the market share of BEVs rising dramatically from 0.8% in 2015 to 21.3% in 2022 (NEA, 2022) (Fig. 1). This trend indicates that the EV market in the Netherlands is transitioning from the innovation stage to the early adoption stage (Rogers, 2003), where the characteristics and considerations of adopter groups may differ. Understanding how this transition unfolds and how household decisions regarding fleet composition influence the diffusion of different EV types is crucial.

3.2. Data

The data used in this study were derived from the Dutch National Travel Survey (DNTS) (Onderzoek Onderweg in Nederland or ODiN in Dutch). The national survey documents the travel patterns of a representative sample of the Dutch population through daily travel diaries and includes questions about socioeconomic and demographic characteristics. From this survey, we extracted data on household car ownership, car fuel type, and residential location at the four-digit postcode

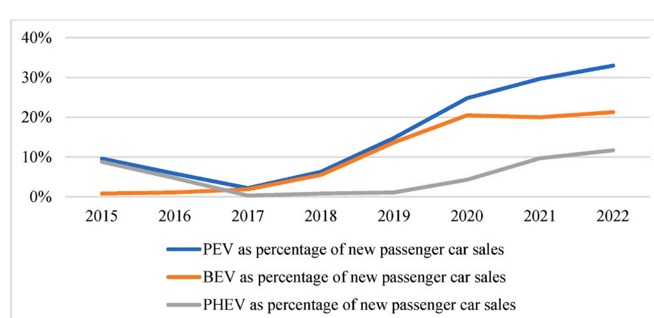

Fig. 1. PEVs, BEVs, and PHEVs as a percentage of new car sales from 2015 to 2020 in the Netherlands (data source: NEA (2021)).

(PC4) level, which aggregates several six-digit postcode (PC6) areas. To increase our sample size, particularly the number of EV adopters, we pooled data from 2018 to 2019. Additionally, to investigate developments in the evolving EV market, we compared data from 2018 to 2019 with data from 2020.

We considered privately owned, leased, and company cars as the vehicles adopted by households. In the DNTS, "leased car" and "company car" are combined into a single category labeled "leased/company car." Accordingly, we used "leased/company car" to collectively refer to both leased and company cars in this study. A total of 173,580 households were recorded in the DNTS 2018–2020 data; of these, 15.78% were no-car households, 47.93% were one-car households, 28.21% were two-car households, and 8.08% had three or more cars. Due to data availability, we only considered households with up to two cars, excluding households with two leased/company cars, which accounted for just 2.16% of two-car households and 0.73% of car-owning households. This subset represents a substantial proportion (89.68%) of car-owning households. Therefore, in this study, households were classified as having no car, one car, or two cars (excluding two leased/company cars). Furthermore, only individuals aged 18 or older were included in the study sample, as they are legally eligible to hold a driver's license. After removing records with missing values, the final sample consisted of 125,443 households.

3.2.1. *Definition of household segments*

We identified nine household types based on different car fleet compositions (Table 1). Specifically, we categorized households as follows.

- No-car households
- One-ICEV households
- One-HEV households
- One-PHEV households
- One-BEV households
- ICEV+ households (two ICEVs)
- HEV+ households (an HEV and either an ICEV or another HEV)
- PHEV+ households (a PHEV and either an ICEV, HEV, or another PHEV)
- BEV+ households (a BEV and any other car type).

We rank cars by increasing levels of electrification: ICEV, HEV, PHEV, and BEV. In most cases, an HEV, PHEV, or BEV is combined with an ICEV to form HEV+, PHEV+, and BEV+ households, respectively.

3.2.2. *Explanatory variables*

Guided by the relevant literature and constrained by data availability, we selected various socioeconomic, demographic, and built environment attributes to describe household characteristics (Table 2). We assumed that individual factors, such as age and education, represent the overall socioeconomic profile of the household.

Age was grouped into six categories: 18–29, 30–39, 40–49, 50–59, 60–69 and ≥70 years old. Education levels were categorized into three groups: low (no formal training, primary education, lower vocational education); moderate (secondary vocational education); and high (higher vocational education, university degree). Households were also categorized by the number of adults (aged over 18) into three groups: one adult; two adults; and three or more adults. Similarly, households were divided into three categories based on the number of children under six years old: those with no young children; one young child; and those with two or more young children. For households with older children (aged six to 17) we used three categories: no older children; one older child; and two or more older children. Household disposable income was divided into five quintiles.

Urbanization degree, based on address density at the PC4 level, was classified into four categories: extremely urbanized (≥2,500 addresses per km^2); highly urbanized (1,500–2,000 addresses/km^2); moderately urbanized (1,000–1,500 addresses/km^2); and barely or not urbanized (<1,000 addresses/km^2). The density of supermarkets and grocery stores refers to the average number of stores within 1 km by road for all residents of a PC4 area. Walkability and cycling accessibility to train stations were defined by the presence of at least one station within 1 km (Guerra et al., 2012) and within 1–4 km, respectively. If a train station was within 1 km, the walkability score for that area was coded as 1; otherwise, it was coded as 0.

3.3. *Modeling approach*

Our primary focus was to identify the determinants of household fleet composition choices. First, we conducted descriptive analyses to examine the socioeconomic, demographic, and built environment attributes across different household segments. Second, to test whether the frequency distribution of categorical variables differed significantly between the two timeframes (2018–2019 vs. 2020), we used Chi-square ($\chi 2$) tests of independence for larger sample sizes and Fisher's exact tests when the assumptions of the $\chi 2$ test were not met, such as with small sample sizes or expected cell counts below five (Altman, 1990; Fisher et al., 2011). For continuous variables, we used independent t-tests.

Third, to examine the correlation between socioeconomic and demographic characteristics, built environment factors, and household fleet size and composition choices, we employed nested logit (NL) regression models. The NL model was chosen to account for possible correlations between the nine household car fleet alternatives due to unobserved variables. For example, one- and two-car fleet alternatives may be correlated, as could alternatives involving similar car types (e.g., BEVs in one- and two-car households). To capture these effects, we tested various nested structures. The Pandas Biogeme package in Python (Bierlaire, 2003) was used for modeling estimation. Finally, using no-car household as the reference category in the NL model, we determined that the four two-car household choices (ICEV+, HEV+, PHEV+, and BEV+) in the same nested layer were the most appropriate (see Fig. 2).

Table 1
Explanation and definition of households based on car fleet composition (Note: The advanced car is defined by the highest level of electrification within the car fleet.).

Category	Household type	Fleet size	Type of advanced car	Sample size		
				2018–2019	2020	Total
No-car households	No car	0	–	13,245	8,140	21,385
One-car households	ICEV	1	ICEV	41,116	23,086	64,202
	HEV	1	HEV	1,295	972	2,267
	PHEV	1	PHEV	238	200	438
	BEV	1	BEV	103	241	344
Two-car households	ICEV+	2	ICEV	21,782	11,880	33,662
	HEV+	2	HEV	946	681	1,627
	PHEV+	2	PHEV	514	317	831
	BEV+	2	BEV	238	449	687
Total				79,477	45,966	125,443

Table 2
Descriptive statistics of the socioeconomic and demographic characteristics of different households and the attributes of their built environment in 2018–2020 (pooled data).

	Household category	No-car	One-ICEV	One-HEV	One-PHEV	One-BEV	ICEV+	HEV+	PHEV+	BEV+
Sample size		21,384	64,202	2,267	438	344	33,662	1,627	831	687
		% per category	% per category	% per category	% per category	% per category	% per category	% per category	% per category	% per category
Year	2018–2019	61.94	64.04	57.12	54.34	29.94	64.71	58.14	61.85	34.64
	2020	38.06	35.96	42.88	45.66	70.06	35.29	41.86	38.15	65.36
Ownership status of household car fleets	One-car household: owned	–	94.21	92.46	44.29	18.31	–	–	–	–
	One-car household: leased/company	–	5.79	7.54	55.71	81.69	–	–	–	–
	Two-car household: two owned, one advanced	–	–	–	–	–	–	65.52	31.53	16.59
	Two-car household: two owned, both advanced	–	–	–	–	–	73.87	4.55	0.60	0.44
	Two-car household: one advanced owned and one leased/company	–	–	–	–	–	–	5.90	2.29	2.91
	Two-car household: one owned and one advanced leased/company	–	–	–	–	–	–	14.87	60.05	74.24
	Two-car household: one owned and one leased/company, both advanced	–	–	–	–	–	26.13	9.16	5.54	5.82
Age	18–29 years old	30.31	12.63	7.85	10.96	18.90	17.13	11.43	13.48	12.52
	30–39 years old	15.05	14.03	13.28	20.32	28.49	17.66	15.86	14.92	19.07
	40–49 years old	10.96	14.58	13.59	27.17	22.09	20.85	19.55	32.49	33.19
	50–59 years old	11.97	15.38	13.45	20.55	18.02	22.17	23.17	24.07	24.16
	60–69 years old	11.63	18.77	22.81	14.38	8.14	14.43	18.87	11.91	9.02
	70 years old and above	20.08	24.61	29.03	6.62	4.36	7.75	11.12	3.13	2.04
Education	Lower education	29.91	28.40	22.32	7.08	4.65	16.29	13.58	8.78	4.66
	Medium education	29.17	31.67	24.48	26.26	18.60	37.10	29.99	28.04	26.20
	Higher education	40.92	39.93	53.20	66.67	76.74	46.61	56.42	63.18	69.14
Number of adults	1	60.28	22.35	16.32	17.81	22.09	2.97	2.77	1.56	2.04
	2	34.43	65.58	73.36	69.18	68.31	68.20	71.24	71.72	72.49
	≥3	5.29	12.07	10.32	13.01	9.59	28.83	26.00	26.71	25.47
Number of younger children	0	95.26	90.65	89.85	84.93	85.17	84.12	85.62	83.63	80.06
	1	3.55	6.29	6.70	9.13	9.88	10.21	9.22	11.07	13.10
	≥2	1.19	3.06	3.44	5.94	4.94	5.67	5.16	5.29	6.84
Number of older children	0	91.52	81.96	84.30	72.83	77.03	69.00	71.11	52.23	53.42
	1	4.94	9.15	8.20	9.36	10.17	15.25	14.87	20.70	20.67
	≥2	3.54	8.89	7.50	17.81	12.79	15.75	14.01	27.08	25.91
Household Income	First quintile	38.32	10.58	6.44	4.34	5.52	4.19	3.32	2.05	2.77
	Second quintile	25.27	22.24	14.64	6.85	4.07	9.08	5.84	3.01	3.35
	Third quintile	14.49	21.94	18.53	11.64	8.72	18.20	14.44	7.70	7.42
	Fourth quintile	11.49	23.53	27.00	16.44	19.48	29.23	28.83	18.89	20.23
	Fifth quintile	10.43	21.71	33.39	60.73	62.21	39.29	47.57	68.35	66.23
Urbanization degree	Extremely urbanized	50.15	25.36	28.89	37.21	50.00	15.81	20.65	18.17	22.71
	Highly urbanized	28.61	32.03	33.79	29.00	26.45	30.11	33.44	30.93	29.40
	Moderately urbanized	9.14	16.43	16.23	13.93	11.63	18.76	20.28	22.02	23.29
	Barely or not urbanized	12.10	26.18	21.09	19.86	11.92	35.32	25.63	28.88	24.60
Walkability of train stations	No	83.72	91.89	92.06	89.50	86.92	95.10	95.64	95.67	95.34
	Yes	16.28	8.11	7.94	10.50	13.08	4.90	4.36	4.33	4.66
Cycling accessibility of train stations	No	37.66	44.38	42.17	37.67	37.79	50.51	45.73	49.94	45.41
	Yes	62.34	55.62	57.83	62.33	62.21	49.49	54.27	50.06	54.59
		Avg. (S.D.)	Avg. (S.D.)	Avg. (S.D.)	Avg. (S.D.)	Avg. (S.D.)	Avg. (S.D.)	Avg. (S.D.)	Avg. (S.D.)	Avg. (S.D.)
Number of supermarkets and grocery stores		21.36 (24.26)	10.84 (14.46)	10.22 (13.39)	13.73 (17.39)	16.44 (19.75)	7.28 (9.39)	7.75 (10.10)	7.16 (9.65)	8.27 (10.80)

This selection was based on the requirement that the dissimilarity parameters of the nested layer fall between 0 and 1, and the model's goodness-of-fit was assessed using the log-likelihood value. The utility functions for each of the nine household alternatives are specified as linear functions of the explanatory variables, as shown in the equation below.

$$U_j = ASC_j + \sum_{k=1}^{K} \beta_k X_{kj}$$

where U_j is the utility associated with the household alternative *j, and* ASC_j is the alternative-specific constant for alternative *j*. β_k represents the coefficient for explanatory variable *k*, and X_{kj} is the value of explanatory variable *k* for alternative *j*.

Each alternative within nest *i* has an associated availability condition Av_j, which indicates whether the alternative is available. The nested logit model with one nest can be represented as:

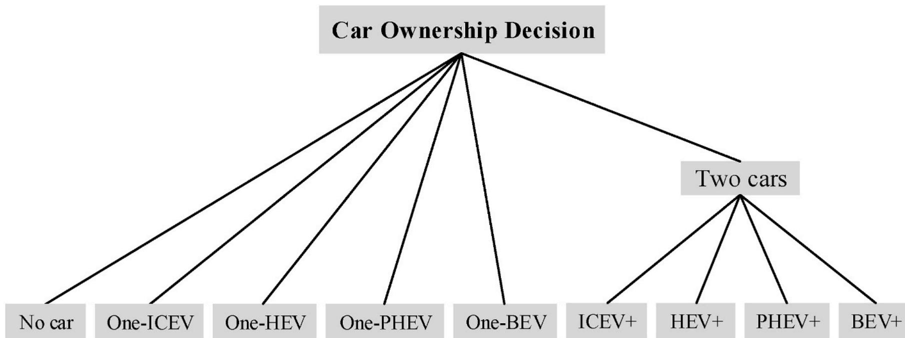

Fig. 2. Nested logit structure for household car fleet choice.

$$P_j = \frac{e^{V_j/\lambda}}{\sum_\iota V_\iota/\lambda} \cdot Av_j$$

where P_j is the probability of choosing alternative j, and λ is the nesting parameter for the nest. V_j represents the utility of alternative j and Av_j indicates the availability of alternative j. ι represents each alternative within the nest for which the probabilities are being calculated. The denominator sums over all alternatives within the nest. For the no-car household, the probability P_0 is not explicitly modeled, as it serves as the reference category and is assumed to have a probability of 0.

Based on the basic model, we estimated five additional NL models to capture the evolving trend in EV adoption by new user groups. In these models, age, education, household size (i.e., number of adults and children), household income, and built environment attributes were included as interaction terms with the 2020 dummy variable, respectively.

4. Results

4.1. Descriptive analysis

Table 2 presents the descriptive statistics of the socioeconomic and demographic characteristics, as well as the built environment across households from 2018 to 2020. Different ownership patterns emerged across car types, with similar trends observed in both one- and two-car households. ICEVs and HEVs were predominantly privately owned, while PHEVs and BEVs were more commonly leased/company cars. In two-car households, ICEV+ and HEV+ households typically owned two cars. In contrast, PHEV+ and BEV+ households usually had one privately owned and one leased/company car, with the PHEV and BEV typically being the leased/company car. The percentage of leased/company PHEVs and BEVs, particularly BEVs, was higher than that of their privately owned counterparts. Furthermore, BEVs and PHEVs were more frequently adopted in two-car households compared to one-car households, unlike ICEVs and HEVs.

No-car households tended to be younger than those with cars, often because individuals were still in school or had not yet started families, which may explain the lower level of car ownership. Additionally, among households with the same fleet size, those with BEVs and PHEVs, especially BEVs, were generally younger compared to those with ICEVs and HEVs. However, this age effect was less pronounced in two-car households. Interestingly, in households with ICEVs and HEVs, two-car households were relatively younger than one-car households. Conversely, for households with BEVs and PHEVs, two-car households were relatively older than one-car households.

In terms of education levels, there was no significant difference between adults in no-car households and one-ICEV households. However, households with HEVs, PHEVs, and BEVs showed a clear trend toward higher education levels. In particular, one-car households with a BEV or PHEV, especially BEV households, had the highest share of highly educated adults.

Compared to households with cars, no-car households had the largest proportion of single-adult households. Two-car households were more likely to have two adults than one-car households. Furthermore, households with cars were more likely to have younger children compared to no-car households, and similarly, they were also more likely to have older children. Specifically, two-car households, especially those with a BEV or PHEV, were more likely than one-car households to have at least two older children.

The highest proportion of no-car households was found in the low-income bracket. Conversely, two-car households tended to be wealthier than one-car households with the same advanced car type. In particular, households with PHEVs and BEVs were predominately composed of affluent households, compared to those with HEVs and ICEVs.

More than half of no-car households resided in extremely urbanized areas. One-car households were more likely to live in highly urbanized areas, including extremely and strongly urbanized regions. Conversely, two-car households with the same advanced car type were less likely to reside in highly urbanized areas. Among households with the same fleet size, BEV users had the highest proportion of living in highly urbanized areas, followed by a slightly lower proportion of PHEV, HEV, and ICEV users, respectively.

In addition, we utilized Chi-square tests or Fisher's exact tests to assess significant changes in the categorical household characteristics between 2018–2019 and 2020 (Table 3). Our analysis revealed significant shifts in car ownership patterns for one-PHEV, one-BEV, and PHEV+ households. Specifically, compared to 2018–2019, PHEVs were increasingly owned and less frequently leased by both one- and two-car households in 2020. Conversely, one-car households saw a slight decline in owned BEVs and a slight increase in leased BEVs in 2020. Significant changes in the age distribution were observed in no-car, one-ICEV, ICEV+, and one-BEV households. Notably, the proportion of middle-aged individuals (40–59 years old) increased in one-BEV households, while a higher number of younger individuals (30–39 years old) were without a car in 2020 compared to 2018–2019. An aging trend was also observed among ICEV users in both one- and two-car households over the study period. Furthermore, there was a notable rise in the percentage of higher-educated households in no-car, one-ICEV, and ICEV+ households, And the proportion of single-adult households increased significantly in one-ICEV households. No significant changes were observed in the distribution of younger children across households between 2018–2019 and 2020. However, there was a significant increase in the proportion of households without older children, particularly in one-ICEV and PHEV+ households. There were no significant changes in income distribution among households between 2018–2019 and 2020. Finally, there was a noteworthy increase in the percentage of no-car, one-ICEV, ICEV+, and HEV+ households residing in extremely urbanized areas in 2020 compared to 2018–2019. Additionally, the percentage of PHEV+ households residing in extremely urbanized areas and barely or not urbanized areas increased in 2020.

Table 3
Chi-square ($\chi 2$) test or Fisher's exact test, and T-test for the significance of the change in the distribution of variables. (Fisher's exact tests conducted and mentioned in the value area).

Variable		No-car household	One-ICEV households	One-HEV households	One-PHEV households	One-BEV households	ICEV+ households	HEV+ households	PHEV+ households	BEV+ households
Ownership status	χ^2 test	N/A	0.647	0.205	33.375	4.080	0.147	4.302	Fisher	Fisher
	Df		1	1	1	1	1	4	N/A	N/A
	Sig				***	*			***	
Age	χ^2 test	15.165	63.922	6.286	10.712	Fisher	20.868	3.362	7.511	Fisher
	Df	5	5	5	5	N/A	5	5	5	N/A
	Sig	**	***			*	***			
Education	χ^2 test	33.379	46.378	1.837	2.641	Fisher	21.472	0.669	1.605	0.448
	Df	2	2	2	2	N/A	2	2	2	2
	Sig	***	***				***			
Number of adults	χ^2 test	1.62	6.29	3.117	5.152	0.466	0.247	0.764	Fisher	Fisher
	Df	2	2	2	2	2	2	2	N/A	N/A
	Sig		*							
Number of younger children	χ^2 test	4.588	2.094	0.422	0.612	4.745	3.205	1.542	0.349	3.448
	Df	2	2	2	2	2	2	2	2	2
	Sig									
Number of older children	χ^2 test	0.026	13.438	0.039	4.972	1.255	1.313	1.085	6.625	4.791
	Df	2	2	2	2	2	2	2	2	2
	Sig		**						*	
Household income	χ^2 test	8.515	5.745	3.903	3.138	Fisher	3.195	2.442	8.177	5.587
	Df	4	4	4	4	N/A	4	4	4	4
	Sig									
Urbanization degree	χ^2 test	72.279	92.723	0.576	2.258	1.959	60.701	8.756	8.699	1.051
	Df	3	3	3	3	3	3	3	3	3
	Sig	***	***				***		*	
Walkability of train stations	χ^2 test	15.501	5.557	0.794	0.000	0.000	2.274	0.000	1.286	0.000
	Df	1	1	1	1	1	1	1	1	1
	Sig	***	*							
Cycling accessibility of train stations	χ^2 test	1.355	2.591	0.302	0.133	0.011	1.473	0.156	0.013	0.302
	Df	1	1	1	1	1	1	1	1	1
	Sig									
Number of supermarkets and grocery stores	T-test	126.48	183.06	34.99	16.07	15.08	134.48	29.42	20.27	19.14
	Df	21400.14	64634.35	2266.63	437.01	343.01	33944.07	1626.57	830.16	686.09
	Sig.	***	***	***	***	***	***	***	***	***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05.

4.2. Model results

The results of the NL model, presented in Table 4, illustrate how socioeconomic and demographic characteristics, as well as built environment attributes are associated with households' car ownership choices. The maximum variance inflation factor (VIF) value is 1.482, indicating minimal multicollinearity between variables.

4.2.1. Socioeconomic and demographic characteristics

The NL model results indicate that as age increases, households are more likely to own cars of any type, whether as single vehicles or part of a fleet. This trend holds across various configurations, including both one- and two-car households regardless of whether the vehicle is the sole car or combined with others. Specifically, ownership of one ICEV or one HEV increases with age, peaking around 60–69 years old. For ICEV+ and HEV+ households, peak ownership occurs around 50–59 years old. In the case of BEVs and PHEVs, households with one PHEV or one BEV peak at ages 40–49 years and 50–59 years, respectively. PHEV+ and BEV+ households reach their peak at 50–59 years old. Overall, these findings suggest that PHEVs and BEVs may appeal more to slightly younger demographics compared to ICEVs and HEVs.

Individuals with higher levels of education are more likely to adopt one or more cars, regardless of fleet size. Notably, the coefficient size indicates that the education effect is strongest for BEV and PHEV adoption, particularly for BEV adoption in single-car households, compared to other car types in both one- and two-car households.

Compared to no-car households, larger households (including those with more adults, younger children, and older children) are more likely to own one or more cars, especially in two-car fleets. The regression coefficients indicate minimal differences in the impact of household size on the adoption of ICEVs, HEVs, PHEVs, and BEVs. However, as expected, larger households are more inclined to own multiple cars.

Higher household income levels increase the likelihood of adopting any type of car, particularly for two-car fleets. However, the coefficient size suggests that the effect of higher income is stronger for the adoption of PHEVs and BEVs compared to ICEVs and HEVs within fleets of the same size. This effect is especially pronounced for PHEV adoption in one-car households.

4.2.2. Built environment attributes

In general, as urbanization decreases, the likelihood of car ownership increases. However, this trend does not apply to households with only

Table 4
Nested logit (NL) regression results for household fleet choice (no-car households are the reference category).

	One-ICEV		One-HEV		One-PHEV		One-BEV		ICEV+		HEV+		PHEV+		BEV+	
Variable	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.
(Intercept)	−1.970	***	−6.520	***	−8.950	***	−8.400	***	−5.530	***	−5.940	***	−6.090	***	−6.180	***
Year																
2018–2019 (ref.)																
2020	−0.047	*	0.217	***	0.338	**	1.330	***	−0.001		0.027		0.012		0.136	***
Age																
18–29 years old (ref.)																
30–39 years old	0.498	***	0.725	***	0.741	***	0.493	**	0.562	***	0.586	***	0.540	***	0.568	***
40–49 years old	0.776	***	1.120	***	1.290	***	0.525	**	0.880	***	0.909	***	0.893	***	0.912	***
50–59 years old	0.937	***	1.240	***	1.240	***	0.540	**	1.010	***	1.050	***	1.010	***	1.020	***
60–69 years old	1.260	***	1.950	***	1.230	***	0.052		0.951	***	1.020	***	0.953	***	0.930	***
≥70 years old	1.030	***	1.860	***	0.350		−0.688	*	0.148	***	0.237	***	0.090		0.049	
Education																
Low education (ref.)																
Medium education	0.344	***	0.403	***	1.020	***	0.851	**	0.574	***	0.582	***	0.582	***	0.639	***
High education	0.298	***	0.725	***	1.200	***	1.430	***	0.517	***	0.554	***	0.551	***	0.624	***
Number of adults																
1 (ref.)																
2	1.330	***	1.690	***	1.390	***	1.280	***	3.180	***	3.190	***	3.210	***	3.180	***
≥3	1.840	***	2.170	***	2.040	***	1.500	***	4.400	***	4.410	***	4.430	***	4.410	***
Number of younger children																
0 (ref.)																
1	0.338	***	0.528	***	0.516	**	0.258		0.632	***	0.631	***	0.650	***	0.656	***
≥2	0.735	***	0.982	***	1.340	***	0.748	**	1.230	***	1.240	***	1.270	***	1.280	***
Number of older children																
0 (ref.)																
1	0.451	***	0.470	***	0.319		0.482	*	0.645	***	0.658	***	0.719	***	0.700	***
≥2	0.675	***	0.599	***	1.170	***	0.859	***	1.080	***	1.080	***	1.180	***	1.160	***
Household income																
First quintile (ref.)																
Second quintile	0.851	***	0.814	***	0.798	**	0.135		0.999	***	0.975	***	0.953	***	0.937	***
Third quintile	1.410	***	1.630	***	1.660	***	1.180	***	2.070	***	2.070	***	2.040	***	2.010	***
Fourth quintile	1.720	***	2.190	***	2.140	***	2.040	***	2.770	***	2.790	***	2.790	***	2.760	***
Fifth quintile	1.830	***	2.520	***	3.500	***	3.180	***	3.350	***	3.380	***	3.490	***	3.440	***
Urbanization degree																
Extremely urbanized (ref.)																
Strongly urbanized	0.925	***	0.527	***	0.865	***	0.193		1.540	***	1.480	***	1.520	***	1.500	***
Moderately urbanized	0.755	***	0.530	***	0.603	***	0.278		1.220	***	1.200	***	1.230	***	1.230	***
Not or hardly urbanized	0.468	***	0.338	***	0.313	*	0.051		0.787	***	0.769	***	0.781	***	0.763	***
Number of supermarkets and grocery stores	−0.227	***	−0.349	***	−0.211	***	−0.224	***	−0.522	***	−0.522	***	−0.525	***	−0.512	***
Walkability of train stations	−0.196	***	−0.186	*	0.046		−0.125		−0.510	***	−0.534	***	−0.535	***	−0.534	***
Cycling accessibility of train stations	−0.110	***	−0.096		0.109		−0.109		−0.272	***	−0.269	***	−0.283	***	−0.270	***
Dissimilarity	0.112	***														
Model Fit																
Init log-likelihood:	−275624.20															
Final log-likelihood:	−122066.10															
Final gradient norm:	0.750															
Number of iterations:	105															

Signif. codes: 0 ’***’ 0.001 ’**’ 0.01 ’*’ 0.05.

one BEV, where BEV adoption is more prevalent in urban areas. This effect is even stronger in two-car households.

The estimated effect of supermarket and grocery store density suggests that as the availability of nearby amenities decreases, the likelihood of car ownership increases. Compared to no-car households, households with cars—particularly those with two cars—are less likely to live within walking or cycling distance from a train station, resulting in lower public transport accessibility. However, this effect is not observed for households with one PHEV or BEV, indicating that PHEV and BEV ownership is less influenced by proximity to public transport.

Overall, as urbanization decreases, the availability of convenience facilities and public transit accessibility also decreases, leading to a higher probability of car ownership. This negative urbanization effect is more pronounced for households with two cars compared to single-car households. However, the effect is less evident for households with one BEV and, to some extent, one PHEV.

4.2.3. Changes in determinants

In 2020, Dutch households were more likely to own an HEV or a PHEV as their sole car, or a BEV either as a single car or as part of a multi-car fleet, after accounting for socioeconomic, demographic, and built environment attributes. This finding aligns with the observed increase in PHEV and BEV sales. We reference five additional NL models in the Appendix (Tables 6–10), where age, education, household size (including adults, younger children, and older children), household income, and built environment attributes were included as interaction terms with the 2020 dummy variable.

The NL model results in Table 6 of the Appendix indicate that in 2020, compared to 2018–2019, the likelihood of car acquisition was less constrained among younger age segments (specifically aged 30–39), except for one-HEV, one-PHEV, and BEV+ households. Notably, this age effect was strongest for households with only one BEV. Furthermore, PHEV adoption in both one- and two-car households, as well as BEV adoption in one-car households, gained traction among individuals aged over 70 in 2020 compared to previous years. These findings suggest that BEV and PHEV adoption has expanded beyond specific age groups and gained popularity across a wider range of demographic segments.

In 2020, the adoption of ICEVs and PHEVs in both one- and two-car households became less dependent on higher education levels compared to 2018–2019 (Appendix, Table 7), suggesting that these vehicle types are being adopted by a wider range of educational backgrounds. The effect of the number of adults or older children on car acquisition choices among households remained consistent from 2018 to 2019 to 2020 (Appendix, Table 8). However, the presence of younger children had less of a restricting effect on car adoption in any fleet type, except for one-HEV and one-PHEV households. This effect was especially pronounced in one-BEV households, suggesting that BEVs have become more appealing to a wider range of households and are increasingly seen as suitable family vehicles.

In 2020, compared to 2018–2019, the adoption of one-ICEV, ICEV+, HEV+, and PHEV+ households became less dependent on higher income levels (Appendix, Table 9), indicating that these vehicle types are becoming more accessible to a broader range of income groups. Finally, in 2020, the negative urbanization effect became stronger for all fleet types, except for one-PHEV, compared to 2018–2019. Additionally, there was no change in the urbanization effect for one-BEV adoption, indicating that BEV adoption in one-car households continues to be primarily an urban phenomenon (Appendix, Table 10).

5. Discussion and conclusion

This study examined EV adoption patterns and trends, distinguishing between ICEVs, HEVs, PHEVs, and BEVs. We examined these choices both as sole family cars and as part of a household car fleet. Households were categorized into nine types based on their car fleet composition. Descriptive analysis highlighted differences in socioeconomic and demographic characteristics, as well as built environment attributes, across these household groups. NL models were employed to explore how these factors are correlated with fleet size and type choices.

5.1. Key findings

5.1.1. BEV and PHEV adoption and ownership

Our sample reveals that the number of BEV and PHEV adopters increased from 2018 to 2019 to 2020, aligning with the Dutch market share data, which rose from 14.8% in 2019 to 24.8% in 2020 (NEA, 2021), despite a decline in total annual car sales from 450,000 in 2019 to 360,000 in 2020 during the COVID-19 pandemic (Statista, 2021). This suggests increased BEV and PHEV ownership alongside a decrease in ICEV ownership in 2020, indicating growing consumer interest in EVs and a shift toward electric driving.

Several factors contribute to this rising adoption of BEVs and PHEVs. First, environmental awareness has steadily increased as the transition from fossil fuels to electricity gains momentum (ANWB.nl, 2021a). Second, the lower operating and total ownership cost of EVs, compared to ICEVs, further encourages adoption, particularly with rising fuel prices, which could influence future EV adoption rates. Third, government subsidies for purchasing or leasing new or second-hand BEVs and PHEVs in the Netherlands have made these vehicles more affordable (ANWB.nl, 2021c). Fourth, technological improvements have increased driving ranges and reduced charging times, making BEVs more practical for everyday use. For example, the average driving range of a BEV rose from 172 km (107 miles) in 2017 to 333 km (207 miles) in 2021 (ANWB.nl, 2021a). Finally, the rapidly growing charging network, including both regular- and fast-charging stations, has enhanced charging opportunities and reduced charging time (Ashkrof et al., 2020).

Nevertheless, we found that the percentage of leased or company BEVs and PHEVs is higher than that of privately-owned counterparts, which contrasts with the USA, where BEVs and PHEVs are primarily purchased by private individuals (Contestabile et al., 2020). This suggests that widespread private EV ownership may still be a long way off among Dutch drivers. One reason is that BEVs and PHEVs are undergoing rapid technological advancements, leading people to prefer leasing over purchasing due to concerns about investing in potentially outdated technology and uncertain resale values. Additionally, subsidies for leasing BEVs and PHEVs encourage this trend (Wallbox, 2021). The percentage of leased BEVs in one-car households increased, potentially due to subsidies introduced on July 1, 2020, for private leasing of BEVs (ANWB.nl, 2021b). Furthermore, employers in the Netherlands are increasingly encouraging employees to use sustainable transportation modes, such as EVs (AD.nl, 2021), which partly explains why higher-educated or higher-income individuals are more likely to drive EVs. Finally, despite the lower total cost of ownership compared to ICEVs, the relatively high purchase price of EVs remains a significant barrier to adoption in the Netherlands (ANWB.nl, 2021a). Similar sentiments are observed in the UK, where drivers prioritize the high purchase cost over lower operating costs (Mandys, 2021). Moreover, BEVs and PHEVs are almost exclusively sold new in the Netherlands, with a limited second-hand market, while 55% of Dutch motorists drive second-hand cars (ANWB.nl, 2021a). In this context, leasing offers a viable option for those who want to drive a BEV or PHEV without purchasing one (Liao et al., 2018). Therefore, it is reasonable that private and company-leased BEVs and PHEVs predominantly account for their adoption in the Netherlands.

5.1.2. Determinants of EV adoption in household car fleet decisions

Young people in both one- and two-car households are more inclined to adopt PHEVs and BEVs over ICEVs and HEVs. This finding partially aligns with Plötz et al. (2014), who found that BEV adopters in Germany are predominantly within the 30–50 age group.

As education levels increase, individuals are more likely to own multiple cars. This finding aligns with (Rith et al., 2019), who found that in the Philippines, highly educated household heads were more willing to acquire additional ICEVs compared to those with lower education levels. Our analysis revealed varying effects of education levels on EV adoption preferences. Specifically, our descriptive analysis showed that households with BEVs, followed by PHEVs, had the highest proportion of highly educated adults compared to those with ICEVs and HEVs at the same fleet levels. Previous research supports this, with highly educated individuals being more inclined toward BEV and PHEV adoption in countries such as the Netherlands (Peters et al., 2018), Canada (Erutku, 2020), Estonia (Joller, 2020), Ireland (Mukherjee and Ryan, 2020), and the USA (Gehrke and Reardon, 2021).

Additionally, our model results indicate that the effect of higher education is strongest for BEV adoption in single-car households compared to other vehicle types. This may be because highly educated individuals are often early adopters of new technologies and are environmentally conscious (Plötz et al., 2014), with environmentalism or social innovation seen as status symbols (White and Sintov, 2017). This finding aligns with research suggesting that BEV owners and lessees place greater importance on the technological and environmental aspects of vehicles compared to PHEV owners and lessees (Lane et al., 2018).

Households with more adults and children are more likely to own cars of any type, particularly in two-car households. This observation is partly supported by Khan and Habib (2021) and Oakil et al. (2013), who found a correlation between an increasing number of children and higher levels of ICEV ownership. This association may be due to the higher frequency of car use among families with children compared to single-person households (Dieleman et al., 2002). Additionally, this finding aligns with Plötz et al. (2014), who identified multi-person households as the most likely group of first private BEV and PHEV buyers in Germany.

Higher household income levels increase the probability of car acquisition across both one- and two-car households, particularly in the latter case. Similarly, Rith et al. (2019) identified household income as a main factor determining ICEV ownership levels in the Philippines. Our model results also suggest that PHEV and BEV adopters are more likely to have higher income levels compared to ICEV and HEV adopters with the same fleet size. This finding aligns with studies on PEV users in Canada (Eluru et al., 2010), India (Bansal et al., 2018), Estonia (Joller, 2020), and the USA (Gehrke and Reardon, 2021), BEV users in Ireland (Mukherjee and Ryan, 2020) and Norway (Qorbani et al., 2024), and EVs in general in the Netherlands (Peters et al., 2018). Additionally, our model results show a strong correlation between higher household income and BEV and PHEV adoption in both one- and two-car households, particularly for PHEVs.

Our model reveals that as urban density increases, the likelihood of car ownership decreases. This effect is stronger for two-car households and most consistent for ICEV and ICEV+ fleets. This finding aligns with previous research, which indicates that increased residential density, enhanced transit accessibility, and greater access to facilities such as hospitals and markets contribute to reduced reliance on private ICEVs (Anowar et al., 2014b; Rith et al., 2019). Remarkably, our descriptive analysis shows that the largest share of BEV and PHEV users reside in highly urbanized areas. Additionally, according to our NL model results, BEV and PHEV adoption, especially BEVs, predominantly occurs in urban settings in the Netherlands. This contrasts with PEV adoption patterns in the UK (Morton et al., 2018) and Germany (Plötz et al., 2014), where suburban and rural areas witness higher adoption rates. This discrepancy can be attributed to two key factors. First, higher-educated and higher-income groups in the Netherlands, who historically prefer urban living (Groot et al., 2015), also show a preference for PHEVs and BEVs. Second, during the early stages of charging infrastructure deployment in the Netherlands, installations were primarily concentrated in city centers, while approximately 65% of households lacked dedicated parking spaces with charging provisions (Wolbertus & van den Hoed, 2020). Consequently, the availability of charging facilities in areas with high parking demand made BEVs and PHEVs particularly appealing in urban areas, especially when their penetration was low. This urban concentration differs from other contexts, such as in the USA, where EV adoption is largely confined to households in single-family homes (Gehrke and Reardon, 2021), and Canada, where EV adoption negatively correlates with individuals who have short commutes (Erutku, 2020).

When considering the model results in Table 4 and Tables 6–10 in the Appendix, several changes between 2018–2019 and 2020 become evident. In 2020, BEV and PHEV adoption in both one- and two-car households became less restricted to specific age groups, showing a more even distribution across age cohorts compared to 2018–2019. Regarding the differences in PHEV and BEV adoption between one- and two-car households, our findings suggest that, relative to 2018–2019, PHEV adoption by one-car households in 2020 became less dependent on education. PHEV adoption in two-car households also became less education-dependent and less restricted to households with younger children and those in less urbanized areas. In 2020, BEV adoption in one-car households became less confined to households with younger children compared to previous years. BEV adoption in two-car households became less dependent on higher education, less restricted to households with younger children, and increasingly popular among households in less urbanized areas. Additionally, we found that PHEV and BEV adoption in two-car households, compared to one-car households, appeals to a broader user group. This partially supports the hypothesis proposed at the start of this paper, suggesting that current EV adopters differ from early adopters, indicating that EV user segments are broadening. Overall, different types of EVs are diffusing into various population segments in terms of age, household composition, and the built environment.

However, these findings also suggest that certain changes occurred between 2018–2019 and 2020, distinguishing PHEVs from BEVs and one-car from two-car fleets. First, PHEV adoption in two-car households became less income-dependent, while PHEV adoption in one-car households and BEV adoption in both one- and two-car households remained income-dependent. Second, PHEV adoption in both one- and two-car households, as well as BEV adoption in two-car households, became less education-dependent. However, higher education still significantly correlates with BEV adoption in one-car households. Finally, BEV adoption in one-car households continues to be predominantly an urban phenomenon. These findings suggest that the uptake of PHEVs and BEVs among specific socio-economically and geographically defined groups still requires further attention. The effects of the year 2020 on household fleet choice relative to 2018–2019 data are summarized in Table 5.

5.2. Expected development paths for different cars

Our analysis revealed a substantial increase in the adoption rate of EVs in the Netherlands from 2018 to 2020, while the adoption of ICEVs saw a slight increase. Based on these empirical insights, the Dutch context, and relevant policies, we anticipate three distinct development paths for the market diffusion of different vehicle types over the next decade, distinguishing between various types of EVs (Fig. 3).

As BEV adoption is currently in the take-off stage and all new cars sales in the Netherlands from 2030 onward must be fully electric (IenW, 2020), we anticipate that BEV diffusion will follow the Type I development path. BEV sales in the Netherlands have been steadily rising since early 2017, growing from 2% of all new car sales in 2017 to 20.5% in 2020 (NEA, 2021). This significant increase in BEV market share suggests that BEV-promoting policies have successfully supported the transition to electric vehicles, with momentum building in 2020. Our findings also indicate that a broader range of demographic groups is becoming interested in acquiring BEVs. With strong policies favoring BEV adoption over other EV types and the ongoing expansion of charging infrastructure, BEVs are expected to reach the peak of Rogers' diffusion curve and account for the majority of new car sales by 2030.

PHEV adoption is expected to decline in the Netherlands by 2030, given the policy mandating that all new cars must be fully electric by that time. Therefore, we anticipate that PHEV diffusion will follow the Type II development path, resembling an inverted U curve. There is already some evidence of this transition. For example, PHEVs gained popularity starting in 2010, accounting for 8.8% of all new car sales in 2015, but this share dropped to 4.7% in 2016 and 0.3% in 2017. This decline may be attributed to the cessation of subsidies for PHEVs in the Netherlands at the end of 2016, prompting Dutch drivers to choose BEVs. However, since BEV users often experience range anxiety and face challenges with underdeveloped charging infrastructure (Lane et al., 2018), PHEVs have served as an intermediate solution in the transition to BEVs. Given that the market share of PHEVs in new car sales increased from 1.1% in 2019 to 4.3% in 2020, we may see a slight increase in PHEV adoption over the next decade. However, they are expected to be gradually phased out as the shift toward BEVs progresses.

Until now, ICEVs and HEVs have accounted for the largest market penetration rate and are at the top of Rogers' diffusion curve in the Netherlands. However, due to their reliance on fossil fuels and environmental impact, they are expected to disappear from the Dutch market by 2030. Thus, we expect that ICEV and HEV diffusion will follow the Type III development path.

5.3. Policy implications

The EV transition is experiencing significant changes and dynamics. To further promote widespread EV adoption, policies should target households that have not yet transitioned to EVs. This study offers the following policy implications.

Further incentives are essential to promote EV adoption. While existing policies and incentives have successfully initiated the EV transition, resulting in significant growth in EV market share, our analysis

Table 5
Summary of 2020 effect on household fleet choice compared to 2018–2019 data. (Note: ↓ means a shift to broader user categories).

Indicator	Household category							
	One-ICEV	One-HEV	One-PHEV	One-BEV	ICEV+	HEV+	PHEV+	BEV+
Age	↓ Less restricted by specific age groups	–	↓ Less restricted by specific age groups	↓ Less restricted by specific age groups	↓ Less restricted by specific age groups	↓ Less restricted by specific age groups	↓ Less restricted by specific age groups	↓ Less restricted by specific age groups
Education	↓ Less high education-dependent	–	↓ Less high education-dependent	–	↓ Less high education-dependent	↓ Less high education-dependent	↓ Less high education-dependent	↓ Less high education-dependent
Number of adults	–	–	–	–	–	–	–	–
Number of younger children	↓ ≥2 Younger children	–	–	↓ ≥2 Younger children	↓ ≥2 Younger children	↓ ≥2 Younger children	↓ ≥2 Younger children	↓ ≥2 Younger children
Number of older children	–	–	–	–	–	–	–	–
Household income	↓ Less high income-dependent	–	–	–	↓ Less high income-dependent	↓ Less high income-dependent	↓ Less high income-dependent	–
Urbanization degree	↓ Weakened negative urbanization effect	↓ Weakened negative urbanization effect	–	–	↓ Weakened negative urbanization effect	↓ Weakened negative urbanization effect	↓ Weakened negative urbanization effect	↓ Weakened negative urbanization effect
Density of supermarkets and grocery stores	–	–	–	–	–	–	–	–
Walkability of train stations	–	–	–	–	–	–	–	–
Cycling accessibility of train stations	–	–	–	–	–	–	–	–

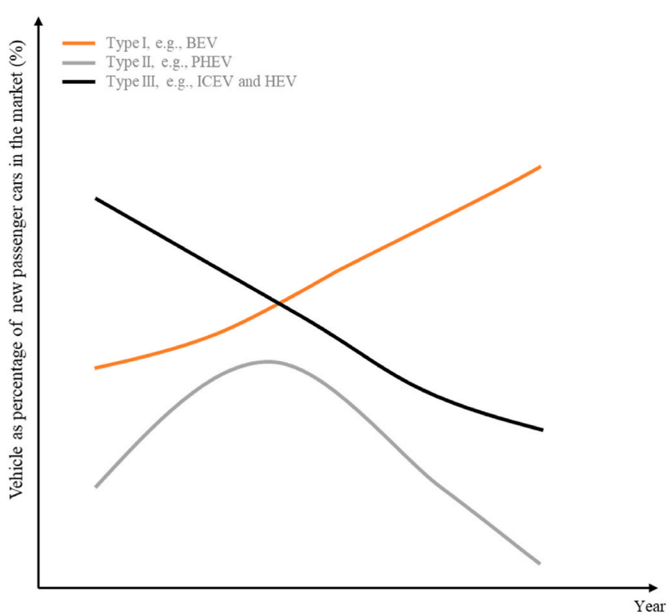

Fig. 3. Conceptual figure showing expected diffusion paths for different vehicle types.

reveals that income remains a key factor in the adoption of BEVs and PHEVs, particularly in one-car households. This indicates that the high purchase prices of BEVs and PHEVs continue to be a significant barrier. As the transition progresses, it will be particularly challenging for the laggards (Rogers, 2003)—those slower to embrace new technologies—to make the shift. Additionally, our findings suggest that many people prefer to lease rather than purchase BEVs and PHEVs. This highlights that, beyond high purchase costs, concerns about resale value and technological uncertainties also influence households' decisions on the ownership of these vehicles. In other words, the decision to adopt an EV involves balancing motivations for adoption with uncertainties about EV technology (Handelsblad, 2021). To overcome financial barriers and mitigate uncertainties, and considering the expected diffusion trends for different EVs outlined in **Section 5.2**, we recommend introducing substantial monetary incentives for both new and second-hand BEVs regardless of ownership status, to encourage broader adoption compared to PHEVs and HEVs. Additionally, based on our analysis showing that income affects BEV and PHEV adoption differently in one- and two-car households, monetary incentives should be tailored accordingly. For example, incentives for BEV adoption could prioritize households with BEV-only fleets over those with mixed fleets (such as those owning both ICEVs and BEVs).

We also recommend promoting alternative business models that reduce costs. Leasing and sharing BEVs and PHEVs, with their more favorable cost structures, offer more affordable alternatives to outright ownership, making these vehicles more accessible, particularly for lower-income groups. Encouraging the development of markets for leased, shared, and second-hand BEVs and PHEVs, along with supportive incentives, is essential. Additionally, as zero-emission zones expand and CO2 emission taxes rise, the value of ICEVs is likely to drop potentially leading to their removal from the second-hand market and creating challenges for the remaining ICEV users. In this scenario, compensation measures could help lower income groups transition from ICEVs to EVs, accelerating the phase-out of ICEVs.

Additionally, given our findings that BEVs, followed by PHEVs, are primarily adopted by households in urbanized areas with established charging infrastructure, we emphasize the importance of expanding charging infrastructure and implementing smart charging technologies. These measures are crucial to alleviating range anxiety and promoting the uptake of BEVs and PHEVs across different regions.

5.4. *Future research recommendations*

While our study provides valuable insights into EV adoption in the context of household car fleet choices, several limitations should be noted. First, this study highlighted existing EV adoption patterns among one- and two-car households in the Netherlands. A critical next step is to explore the nuanced decisions households make when integrating BEVs and PHEVs into their fleets, and how these choices are influenced by social, infrastructural, and market factors. For example, it is important to examine whether households choose to replace ICEVs with BEVs or add BEVs as additional vehicles. Second, our study suggests that the user characteristics and ownership statuses of BEVs and PHEVs differ from those of ICEVs, which may also influence their usage patterns. Accordingly, future research should explore how the usage of BEVs and PHEVs differs from that of ICEVs. Finally, the paper examines trends and changes in EV adoption by comparing data from 2018 to 2019 and 2020. While this comparison provides valuable insights, it is important to acknowledge that some observed differences may be influenced by unobserved factors. Therefore, future research should incorporate more granular longitudinal data, allowing for a more detailed analysis of the dynamics of EV adoption over multiple years. By addressing these future research directions, a more robust and comprehensive understanding of household fleet choices and vehicle adoption can be achieved.

Data availability

The authors do not have permission to share data.

CRediT authorship contribution statement

Linlin Zhang: Conceptualization, Formal analysis, Methodology, Software, Writing – original draft, Writing – review & editing. **Dea van Lierop:** Supervision, Writing – review & editing. **Dick Ettema:** Conceptualization, Methodology, Project administration, Supervision, Writing – review & editing.

Declaration of competing interest

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

Data availability

The authors do not have permission to share data.

Acknowledgments

This work was supported by the China Scholarship Council. We would also like to thank the anonymous reviewers for their constructive feedback.

Appendix

Table 6
NL model with year and age as the interaction terms

	One-ICEV		One-HEV		One-PHEV		One-BEV		ICEV+		HEV+		PHEV+		BEV+	
Variable	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.
(Intercept)	−1.970	***	−6.500	***	−8.780	***	−8.530	***	−5.520	***	−5.950	***	−6.090	***	−6.180	***
Year																
2018–2019 (ref.)																
2020	−0.037		0.159		−0.082		1.520	***	−0.028		0.010		−0.015		0.113	
Age																
18–29 years old (ref.)																
30–39 years old	0.555	***	0.780	***	0.783	***	0.960	**	0.627	***	0.653	***	0.603	***	0.629	***
40–49 years old	0.782	***	1.090	***	1.170	***	0.563		0.893	***	0.928	***	0.913	***	0.937	***
50–59 years old	0.950	***	1.260	***	0.936	***	0.139		0.986	***	1.040	***	0.994	***	0.993	***
60–69 years old	1.260	***	1.940	***	0.914	***	0.334		0.930	***	1.010	***	0.910	***	0.920	***
≥70 years old	0.996	***	1.750	***	−0.199		−0.114		0.063		0.155	**	0.000		−0.052	
Education																
Low education (ref.)																
Medium education	0.343	***	0.403	***	1.020	***	0.842	**	0.573	***	0.581	***	0.581	***	0.638	***
High education	0.298	***	0.726	***	1.200	***	1.420	***	0.517	***	0.555	***	0.552	***	0.626	***
Number of adults																
1 (ref.)																
2	1.330	***	1.690	***	1.390	***	1.270	***	3.180	***	3.190	***	3.210	***	3.180	***
≥3	1.840	***	2.170	***	2.040	***	1.490	***	4.400	***	4.420	***	4.430	***	4.410	***
Number of younger children																
0 (ref.)																
1	0.337	***	0.526	***	0.511	**	0.252		0.631	***	0.630	***	0.648	***	0.655	***
≥2	0.736	***	0.981	***	1.340	***	0.739	**	1.230	***	1.240	***	1.270	***	1.280	***
Number of older children																
0 (ref.)																
1	0.451	***	0.470	***	0.315		0.476	*	0.644	***	0.657	***	0.719	***	0.700	***
≥2	0.674	***	0.597	***	1.170	***	0.846	***	1.080	***	1.080	***	1.180	***	1.160	***
Household income																
First quintile (ref.)																
Second quintile	0.852	***	0.817	***	0.803	**	0.133		1.000	***	0.976	***	0.955	***	0.938	***
Third quintile	1.410	***	1.630	***	1.670	***	1.180	***	2.070	***	2.070	***	2.050	***	2.010	***
Fourth quintile	1.720	***	2.200	***	2.140	***	2.040	***	2.770	***	2.790	***	2.790	***	2.760	***
Fifth quintile	1.830	***	2.530	***	3.510	***	3.170	***	3.360	***	3.390	***	3.500	***	3.450	***
Urbanization degree																
Extremely urbanized (ref.)																
Strongly urbanized	0.467	***	0.338	***	0.311	*	0.051		0.786	***	0.769	***	0.780	***	0.762	***

(*continued on next page*)

Table 6 (*continued*)

Variable	One-ICEV Coef.	Sig.	One-HEV Coef.	Sig.	One-PHEV Coef.	Sig.	One-BEV Coef.	Sig.	ICEV+ Coef.	Sig.	HEV+ Coef.	Sig.	PHEV+ Coef.	Sig.	BEV+ Coef.	Sig.
Moderately urbanized	0.755	***	0.529	***	0.601	***	0.279		1.220	***	1.200	***	1.230	***	1.230	***
Not or hardly urbanized	0.925	***	0.527	***	0.864	***	0.196		1.540	***	1.480	***	1.520	***	1.500	***
Density of supermarkets and grocery stores	−0.227	***	−0.350	***	−0.212	***	−0.224	***	−0.522	***	−0.522	***	−0.525	***	−0.512	***
Walkability of train stations	−0.197	***	−0.185		0.045		−0.127		−0.510	***	−0.534	***	−0.536	***	−0.534	***
Cycling accessibility of train stations	−0.110	***	−0.096		0.107		−0.112		−0.273	***	−0.269	***	−0.283	***	−0.271	***
Interaction terms between Year and Age																
2018–2019 * 18–29 years old (ref.)																
2020 * 30–39 years old	−0.149	*	−0.137		−0.099		−0.741	*	−0.167	*	−0.172	*	−0.163	*	−0.162	
2020 * 40–49 years old	−0.016		0.070		0.301		−0.053		−0.036		−0.048		−0.053		−0.054	
2020 * 50–59 years old	−0.039		−0.042		0.705		0.524		0.060		0.036		0.050		0.075	
2020 * 60–69 years old	−0.010		0.038		0.729		−0.399		0.056		0.052		0.107		0.040	
2020 * ≥ 70 years old	0.095		0.251		1.140	*	−0.845		0.218	**	0.214	**	0.229	*	0.240	*
Dissimilarity	0.113	***														
Model Fit																
Init log-likelihood:	−275624.2															
Final log-likelihood:	−122031.6															
Final gradient norm:	0.726															

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05.

Table 7
NL model with year and education as the interaction terms.

Variable	One-ICEV Coef.	Sig.	One-HEV Coef.	Sig.	One-PHEV Coef.	Sig.	One-BEV Coef.	Sig.	ICEV+ Coef.	Sig.	HEV+ Coef.	Sig.	PHEV+ Coef.	Sig.	BEV+ Coef.	Sig.
(Intercept)	−2.000	***	−6.530	***	−9.290	***	−8.480	***	−5.560	***	−5.950	***	−6.110	***	−6.180	***
Year																
2018–2019 (ref.)																
2020	0.033		0.252	**	1.030	**	1.490	**	0.087		0.112	*	0.142	**	0.222	***
Age																
18–29 years old (ref.)																
30–39 years old	0.498	***	0.725	***	0.744	***	0.495	**	0.563	***	0.585	***	0.543	***	0.568	***
40–49 years old	0.777	***	1.120	***	1.290	***	0.527	**	0.881	***	0.908	***	0.893	***	0.911	***
50–59 years old	0.937	***	1.240	***	1.250	***	0.541	**	1.010	***	1.050	***	1.010	***	1.020	***
60–69 years old	1.260	***	1.950	***	1.240	***	0.052		0.950	***	1.020	***	0.952	***	0.931	***
≥70 years old	1.030	***	1.860	***	0.346		−0.689	*	0.146	***	0.230	***	0.091		0.054	
Education																
Low education (ref.)																
Medium education	0.371	***	0.399	***	1.390	***	0.898		0.593	***	0.598	***	0.614	***	0.649	***
High education	0.353	***	0.762	***	1.580	***	1.550	***	0.584	***	0.619	***	0.637	***	0.692	***
Number of adults																
1 (ref.)																
2	1.330	***	1.690	***	1.390	***	1.270	***	3.180	***	3.190	***	3.210	***	3.180	***
≥3	1.840	***	2.170	***	2.040	***	1.490	***	4.400	***	4.410	***	4.430	***	4.410	***
Number of younger children																
0 (ref.)																
1	0.337	***	0.527	***	0.513	**	0.257		0.631	***	0.631	***	0.648	***	0.654	***
≥2	0.735	***	0.982	***	1.340	***	0.747	**	1.230	***	1.230	***	1.270	***	1.270	***
Number of older children																
0 (ref.)																
1	0.451	***	0.470	***	0.317		0.479	*	0.644	***	0.656	***	0.714	***	0.696	***
≥2	0.674	***	0.598	***	1.170	***	0.855	***	1.080	***	1.080	***	1.180	***	1.150	***
Household income																
First quintile (ref.)																
Second quintile	0.852	***	0.815	***	0.801	**	0.136		1.000	***	0.977	***	0.958	***	0.942	***
Third quintile	1.410	***	1.630	***	1.670	***	1.180	***	2.070	***	2.070	***	2.050	***	2.010	***
Fourth quintile	1.720	***	2.190	***	2.140	***	2.040	***	2.770	***	2.790	***	2.790	***	2.760	***
Fifth quintile	1.830	***	2.520	***	3.510	***	3.170	***	3.360	***	3.380	***	3.490	***	3.440	***
Urbanization degree																
Extremely urbanized (ref.)																
Strongly urbanized	0.467	***	0.337	***	0.311	*	0.048		0.785	***	0.769	***	0.779	***	0.763	***
Moderately urbanized	0.755	***	0.530	***	0.602	***	0.275		1.220	***	1.200	***	1.230	***	1.230	***
Not or hardly urbanized	0.925	***	0.527	***	0.866	***	0.191		1.540	***	1.490	***	1.520	***	1.500	***
Number of supermarkets and grocery stores	−0.227	***	−0.350	***	−0.212	***	−0.224	***	−0.522	***	−0.522	***	−0.525	***	−0.513	***
Walkability of train stations	−0.196	***	−0.186	*	0.047		−0.124		−0.510	***	−0.532	***	−0.533	***	−0.532	***

(*continued on next page*)

Table 7 (*continued*)

Variable	One-ICEV Coef.	Sig.	One-HEV Coef.	Sig.	One-PHEV Coef.	Sig.	One-BEV Coef.	Sig.	ICEV+ Coef.	Sig.	HEV+ Coef.	Sig.	PHEV+ Coef.	Sig.	BEV+ Coef.	Sig.
Cycling accessibility of train stations	−0.110	***	−0.096		0.109		−0.110		−0.272	***	−0.269	***	−0.282	***	−0.270	***
Interaction terms between Year and Education																
2018–2019 * Low education (ref.)																
2020 * Medium education	−0.077		0.003		−0.754		−0.100		−0.053		−0.048		−0.087		−0.047	
2020 * High education	−0.146	**	−0.100		−0.804	*	−0.245		−0.179	**	−0.180	**	−0.232	***	−0.191	**
Dissimilarity	0.105	***														
Model Fit																
Init log-likelihood:	−275624.2															
Final log-likelihood:	−122054.4															
Final gradient norm:	0.737															

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05.

Table 8
NL model with year and number of adults, younger children, and older children as the interaction terms

Variable	One-ICEV Coef.	Sig.	One-HEV Coef.	Sig.	One-PHEV Coef.	Sig.	One-BEV Coef.	Sig.	ICEV+ Coef.	Sig.	HEV+ Coef.	Sig.	PHEV+ Coef.	Sig.	BEV+ Coef.	Sig.
(Intercept)	−1.980	***	−6.590	***	−8.780	***	−8.310	***	−5.530	***	−5.910	***	−6.060	***	−6.100	***
Year																
2018–2019 (ref.)																
2020	−0.012		0.379	***	−0.090		1.210	***	0.002		0.000		−0.008		0.044	
Age																
18–29 years old (ref.)																
30–39 years old	0.498	***	0.726	***	0.744	***	0.498	**	0.563	***	0.586	***	0.542	***	0.568	***
40–49 years old	0.777	***	1.120	***	1.290	***	0.532	**	0.881	***	0.909	***	0.893	***	0.912	***
50–59 years old	0.937	***	1.250	***	1.250	***	0.546	**	1.010	***	1.050	***	1.010	***	1.020	***
60–69 years old	1.260	***	1.950	***	1.240	***	0.057		0.951	***	1.020	***	0.953	***	0.932	***
≥70 years old	1.030	***	1.860	***	0.358		−0.682	*	0.148	***	0.233	***	0.093		0.054	
Education																
Low education (ref.)																
Medium education	0.344	***	0.403	***	1.030	***	0.846	**	0.574	***	0.581	***	0.581	***	0.635	***
High education	0.298	***	0.725	***	1.200	***	1.420	***	0.517	***	0.553	***	0.550	***	0.619	***
Number of adults																
1 (ref.)																
2	1.350	***	1.780	***	1.180	***	1.120	***	3.180	***	3.180	***	3.190	***	3.120	***
≥3	1.830	***	2.230	***	1.980	***	1.300	**	4.380	***	4.380	***	4.380	***	4.340	***
Number of younger children																
0 (ref.)																
1	0.319	***	0.562	***	0.569	*	0.413		0.656	***	0.660	***	0.663	***	0.696	***
≥2	0.875	***	1.130	***	1.660	***	1.520	***	1.390	***	1.380	***	1.430	***	1.480	***
Number of older children																
0 (ref.)																
1	0.482	***	0.444	***	0.219		0.502		0.658	***	0.665	***	0.751	***	0.691	***
≥2	0.700	***	0.599	***	0.990	***	0.658		1.120	***	1.120	***	1.230	***	1.210	***
Household income																
First quintile (ref.)																
Second quintile	0.850	***	0.813	***	0.795	**	0.135		0.999	***	0.976	***	0.955	***	0.941	***
Third quintile	1.410	***	1.630	***	1.660	***	1.170	***	2.070	***	2.070	***	2.040	***	2.010	***
Fourth quintile	1.720	***	2.190	***	2.130	***	2.040	***	2.770	***	2.790	***	2.790	***	2.760	***
Fifth quintile	1.830	***	2.520	***	3.500	***	3.180	***	3.360	***	3.380	***	3.490	***	3.440	***
Urbanization degree																
Extremely urbanized (ref.)																
Strongly urbanized	0.467	***	0.338	***	0.315	*	0.050		0.786	***	0.770	***	0.780	***	0.764	***
Moderately urbanized	0.755	***	0.530	***	0.606	***	0.278		1.220	***	1.210	***	1.230	***	1.230	***
Not or hardly urbanized	0.925	***	0.526	***	0.866	***	0.194		1.540	***	1.490	***	1.520	***	1.500	***
Number of supermarkets and grocery stores	−0.227	***	−0.350	***	−0.210	***	−0.225	***	−0.522	***	−0.522	***	−0.525	***	−0.513	***
Walkability of train stations	−0.197	***	−0.187	*	0.051		−0.120		−0.511	***	−0.533	***	−0.535	***	−0.533	***
Cycling accessibility of train stations	−0.110	***	−0.096		0.106		−0.109		−0.272	***	−0.269	***	−0.283	***	−0.270	***
Interaction terms between Year and household persons																
Year * Number of adults																
2018–2019 * 1 adult (ref.)																
2020 * 2 Adults	−0.052		−0.210		0.495		0.205		−0.001		0.028		0.031		0.108	
2020 * ≥ 3 Adults	0.023		−0.135		0.174		0.294		0.063		0.087		0.127		0.154	
Year * Number of younger children																
2018–2019 * 0 Younger child (ref.)																

(*continued on next page*)

Table 8 (*continued*)

Variable	One-ICEV Coef.	Sig.	One-HEV Coef.	Sig.	One-PHEV Coef.	Sig.	One-BEV Coef.	Sig.	ICEV+ Coef.	Sig.	HEV+ Coef.	Sig.	PHEV+ Coef.	Sig.	BEV+ Coef.	Sig.
2020 * 1 Younger child	0.055		−0.083		−0.112		−0.223		−0.067		−0.078		−0.041		−0.093	
2020 * ≥ 2 Younger children	−0.350	*	−0.369		−0.743		−1.410	**	−0.401	**	−0.374	*	−0.413	**	−0.475	**
Year * Number of older children																
2018–2019 * 0 Older child (ref.)																
2020 * 1 Older child	−0.088		0.052		0.201		−0.061		−0.037		−0.024		−0.097		−0.009	
2020 * ≥ 2 Older children	−0.071		−0.013		0.334		0.227		−0.100		−0.108		−0.132		−0.141	
Dissimilarity	0.106	***														
Model Fit																
Init log-likelihood:	−275624.2															
Final log-likelihood:	−122034.1															
Final gradient norm:	0.668															

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05.

Table 9
NL model with year and household income as the interaction terms

Variable	One-ICEV Coef.	Sig.	One-HEV Coef.	Sig.	One-PHEV Coef.	Sig.	One-BEV Coef.	Sig.	ICEV+ Coef.	Sig.	HEV+ Coef.	Sig.	PHEV+ Coef.	Sig.	BEV+ Coef.	Sig.
(Intercept)	−1.990	***	−6.440	***	−9.020	***	−8.400	***	−5.560	***	−5.960	***	−6.120	***	−6.160	***
Year																
2018–2019 (ref.)																
2020	0.028		0.014		0.499		1.350	**	0.102		0.126		0.154		0.178	*
Age																
18–29 years old (ref.)																
30–39 years old	0.497	***	0.725	***	0.741	***	0.495	**	0.562	***	0.585	***	0.542	***	0.568	***
40–49 years old	0.777	***	1.120	***	1.290	***	0.527	**	0.880	***	0.908	***	0.893	***	0.911	***
50–59 years old	0.937	***	1.250	***	1.250	***	0.542	**	1.010	***	1.050	***	1.010	***	1.020	***
60–69 years old	1.260	***	1.950	***	1.230	***	0.053		0.950	***	1.020	***	0.952	***	0.930	***
≥70 years old	1.030	***	1.860	***	0.345		−0.685	*	0.146	***	0.232	***	0.091		0.053	
Education																
Low education (ref.)																
Medium education	0.343	***	0.402	***	1.020	***	0.844	**	0.574	***	0.581	***	0.581	***	0.635	***
High education	0.298	***	0.724	***	1.200	***	1.420	***	0.517	***	0.553	***	0.550	***	0.620	***
Number of adults																
1 (ref.)																
2	1.330	***	1.690	***	1.380	***	1.270	***	3.180	***	3.190	***	3.210	***	3.180	***
≥3	1.840	***	2.170	***	2.040	***	1.490	***	4.400	***	4.410	***	4.430	***	4.410	***
Number of younger children																
0 (ref.)																
1	0.338	***	0.527	***	0.516	**	0.258		0.632	***	0.632	***	0.649	***	0.656	***
≥2	0.736	***	0.984	***	1.350	***	0.750	**	1.230	***	1.240	***	1.270	***	1.280	***
Number of older children																
0 (ref.)																
1	0.451	***	0.471	***	0.322		0.482	*	0.645	***	0.658	***	0.717	***	0.698	***
≥2	0.675	***	0.599	***	1.180	***	0.858	***	1.080	***	1.080	***	1.180	***	1.150	***
Household income																
First quintile (ref.)																
Second quintile	0.869	***	0.745	***	0.687		0.058		1.020	***	0.982	***	1.000	***	0.921	***
Third quintile	1.440	***	1.490	***	1.530	***	1.170	*	2.110	***	2.110	***	2.070	***	2.040	***
Fourth quintile	1.780	***	2.150	***	2.270	***	2.010	***	2.820	***	2.830	***	2.860	***	2.770	***
Fifth quintile	1.890	***	2.470	***	3.660	***	3.240	***	3.450	***	3.480	***	3.600	***	3.500	***
Urbanization degree																
Extremely urbanized (ref.)																
Strongly urbanized	0.467	***	0.339	***	0.311	*	0.049		0.786	***	0.769	***	0.780	***	0.763	***
Moderately urbanized	0.756	***	0.531	***	0.604	***	0.279		1.220	***	1.210	***	1.230	***	1.230	***
Not or hardly urbanized	0.926	***	0.528	***	0.866	***	0.195		1.540	***	1.490	***	1.520	***	1.500	***
Density of supermarkets and grocery stores	−0.227	***	−0.349	***	−0.212	***	−0.223	***	−0.522	***	−0.522	***	−0.526	***	−0.513	***
Walkability of train stations	−0.195	***	−0.186	*	0.049		−0.120		−0.509	***	−0.532	***	−0.533	***	−0.531	***
Cycling accessibility of train stations	−0.110	***	−0.096		0.110		−0.107		−0.272	***	−0.269	***	−0.283	***	−0.270	***
Interaction terms between Year and Household income																
2018–2019 * First quintile (ref.)																
2020 * Second quintile	−0.049		0.170		0.216		0.102		−0.047		−0.021		−0.129		0.014	
2020 * Third quintile	−0.084		0.328		0.249		−0.003		−0.104		−0.104		−0.071		−0.098	
2020 * Fourth quintile	−0.148	*	0.109		−0.320		0.001		−0.136		−0.129		−0.182		−0.069	
2020 * Fifth quintile	−0.167	**	0.130		−0.366		−0.154		−0.242	**	−0.244	**	−0.288	**	−0.183	
Dissimilarity	0.107	***														

(*continued on next page*)

Table 9 (*continued*)

Variable	One-ICEV Coef.	Sig.	One-HEV Coef.	Sig.	One-PHEV Coef.	Sig.	One-BEV Coef.	Sig.	ICEV+ Coef.	Sig.	HEV+ Coef.	Sig.	PHEV+ Coef.	Sig.	BEV+ Coef.	Sig.
Model Fit																
Init log-likelihood:	−275624.2															
Final log-likelihood:	−122045															
Final gradient norm:	0.722															

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05.

Table 10
NL model with year and built environment attributes as the interaction terms

Variable	One-ICEV Coef.	Sig.	One-HEV Coef.	Sig.	One-PHEV Coef.	Sig.	One-BEV Coef.	Sig.	ICEV+ Coef.	Sig.	HEV+ Coef.	Sig.	PHEV+ Coef.	Sig.	BEV+ Coef.	Sig.
(Intercept)	−1.960	***	−6.470	***	−8.860	***	−8.420	***	−5.510	***	−5.910	***	−6.050	***	−6.100	***
Year																
2018–2019 (ref.)																
2020	−0.060		0.102		0.148		1.360	***	−0.041		0.004		−0.018		0.055	
Age																
18–29 years old (ref.)																
30–39 years old	0.497	***	0.725	***	0.738	***	0.494	**	0.561	***	0.584	***	0.541	***	0.567	***
40–49 years old	0.775	***	1.120	***	1.290	***	0.529	**	0.879	***	0.906	***	0.892	***	0.909	***
50–59 years old	0.936	***	1.240	***	1.240	***	0.542	**	1.010	***	1.050	***	1.010	***	1.020	***
60–69 years old	1.260	***	1.950	***	1.230	***	0.053		0.949	***	1.020	***	0.951	***	0.930	***
≥70 years old	1.030	***	1.860	***	0.344		−0.688	*	0.147	***	0.232	***	0.093		0.055	
Education																
Low education (ref.)																
Medium education	0.343	***	0.403	***	1.020	***	0.846	**	0.574	***	0.581	***	0.581	***	0.635	***
High education	0.298	***	0.725	***	1.200	***	1.420	***	0.517	***	0.552	***	0.549	***	0.618	***
Number of adults																
1 (ref.)																
2	1.330	***	1.690	***	1.380	***	1.270	***	3.180	***	3.190	***	3.200	***	3.180	***
≥3	1.840	***	2.170	***	2.040	***	1.500	***	4.400	***	4.410	***	4.430	***	4.410	***
Number of younger children																
0 (ref.)																
1	0.339	***	0.528	***	0.514	**	0.258		0.632	***	0.632	***	0.650	***	0.655	***
≥2	0.735	***	0.981	***	1.340	***	0.747	**	1.230	***	1.230	***	1.270	***	1.270	***
Number of older children																
0 (ref.)																
1	0.452	***	0.471	***	0.317		0.479	*	0.646	***	0.658	***	0.716	***	0.698	***
≥2	0.676	***	0.598	***	1.170	***	0.856	***	1.080	***	1.080	***	1.180	***	1.150	***
Household income																
First quintile (ref.)																
Second quintile	0.850	***	0.814	***	0.797	**	0.133		0.998	***	0.975	***	0.955	***	0.939	***
Third quintile	1.410	***	1.630	***	1.660	***	1.180	***	2.070	***	2.070	***	2.040	***	2.010	***
Fourth quintile	1.720	***	2.200	***	2.130	***	2.040	***	2.770	***	2.790	***	2.790	***	2.760	***
Fifth quintile	1.830	***	2.530	***	3.500	***	3.170	***	3.350	***	3.380	***	3.490	***	3.440	***
Urbanization degree																
Extremely urbanized (ref.)																
Strongly urbanized	0.410	***	0.237	**	0.332		0.125		0.717	***	0.707	***	0.719	***	0.686	***
Moderately urbanized	0.741	***	0.446	***	0.474	*	0.217		1.200	***	1.190	***	1.220	***	1.180	***
Not or hardly urbanized	0.896	***	0.443	***	0.679	**	−0.126		1.510	***	1.460	***	1.480	***	1.440	***
Density of supermarkets and grocery stores	−0.229	***	−0.339	***	−0.180	**	−0.198		−0.513	***	−0.511	***	−0.522	***	−0.501	***
Walkability of train stations	−0.151	***	−0.092		−0.023		−0.029		−0.488	***	−0.508	***	−0.491	***	−0.526	***
Cycling accessibility of train stations	−0.086	**	−0.107		0.011		−0.091		−0.261	***	−0.257	***	−0.270	***	−0.273	***
Interaction terms between Year and built environment attributes																
Year * Urbanization degree																
2018–2019 * Extremely urbanized (ref.)																
2020 * Strongly urbanized	0.152	**	0.248	*	−0.035		−0.050		0.184	**	0.167	**	0.162	*	0.195	**
2020 * Moderately urbanized	0.031		0.193		0.279		0.104		0.064		0.053		0.016		0.101	
2020 * Not or hardly urbanized	0.076		0.201		0.419		0.482		0.092		0.065		0.104		0.135	
Year * Density of supermarkets and daily grocery stores																
2018–2019 * Density of supermarkets and daily grocery stores (ref.)																
2020 * Density of supermarkets and daily grocery stores	0.005		−0.029		−0.075		−0.039		−0.023		−0.030		−0.010		−0.030	
Year * Walkability of train stations																
2018–2019 * Walkability of train stations (ref.)																

(*continued on next page*)

Table 10 (*continued*)

Variable	One-ICEV Coef.	One-ICEV Sig.	One-HEV Coef.	One-HEV Sig.	One-PHEV Coef.	One-PHEV Sig.	One-BEV Coef.	One-BEV Sig.	ICEV+ Coef.	ICEV+ Sig.	HEV+ Coef.	HEV+ Sig.	PHEV+ Coef.	PHEV+ Sig.	BEV+ Coef.	BEV+ Sig.
2020 * Walkability of train stations	−0.115		−0.227		0.152		−0.167		−0.051		−0.058		−0.114		−0.027	
Year * Cycling accessibility of train stations																
2018–2019 * Cycling accessibility of train stations (ref.)																
2020 * Cycling accessibility of train stations	−0.064		0.021		0.211		−0.043		−0.030		−0.032		−0.033		−0.007	
Dissimilarity	0.105	***														
Model Fit																
Init log-likelihood:	−275624.2															
Final log-likelihood:	−122040.4															
Final gradient norm:	0.755															

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05.

References

AD.nl, 2021. Who still wants a company car? Doom threatens. https://www.ad.nl/auto/wie-wil-er-nog-een-auto-van-de-zaak-de-ondergang-dreigt~a1d4764e/.

Almeida Neves, S., Cardoso Marques, A., Alberto Fuinhas, J., 2019. Technological progress and other factors behind the adoption of electric vehicles: empirical evidence for EU countries. Res. Transport. Econ. 74, 28–39. https://doi.org/10.1016/j.retrec.2018.12.001.

Altman, D.G., 1990. Practical Statistics for Medical Research. Chapman and Hall/CRC.

Anowar, S., Eluru, N., Miranda-Moreno, L.F., 2014a. Alternative modeling approaches used for examining automobile ownership: a comprehensive review. Transport Rev. 34 (4), 441–473. https://doi.org/10.1080/01441647.2014.915440.

Anowar, S., Eluru, N., Miranda-Moreno, L.F., Lee-Gosselin, M., 2015. Joint econometric analysis of temporal and spatial flexibility of activities, vehicle type choice, and primary driver selection. Transport. Res. Rec. 2525, 32–41. https://doi.org/10.3141/2495-04 [Article].

Anowar, S., Yasmin, S., Eluru, N., Miranda-Moreno, F.L., 2014b. Analyzing car ownership in Quebec City: a comparison of traditional and latent class ordered and unordered models. Transportation 41, 1013–1039. https://doi.org/10.1007/s11116-014-9522-9.

ANWB.nl, 2021a. Electric driving monitor 2021, the state of affairs regarding electric driving in The Netherlands. https://www.anwb.nl/belangenbehartiging/duurzaam/elektrisch-rijden-monitor-2021.

ANWB.nl, 2021b. Private leasing of an electric car. https://www.anwb.nl/auto/private-lease/elektrische-auto-private-leasen.

ANWB.nl, 2021c. Subsidy for full electric cars: all the conditions at a glance. https://www.anwb.nl/auto/elektrisch-rijden/subsidie-elektrische-autos.

Ashkrof, P., Homem de Almeida Correia, G., van Arem, B., 2020. Analysis of the effect of charging needs on battery electric vehicle drivers' route choice behaviour: a case study in The Netherlands. Transport. Res. Transport Environ. 78 https://doi.org/10.1016/j.trd.2019.102206.

Bansal, P., Kockelman, K.M., Schievelbein, W., Schauer-West, S., 2018. Indian vehicle ownership and travel behavior: a case study of Bengaluru, Delhi and Kolkata [Article]. Res. Transport. Econ. 71, 2–8. https://doi.org/10.1016/j.retrec.2018.07.025.

Bierlaire, M., 2003. BIOGEME: a free package for the estimation of discrete choice models. In: Swiss Transport Research Conference.

Brückmann, G., Willibald, F., Blanco, V., 2021. Battery Electric Vehicle adoption in regions without strong policies. Transport. Res. Transport Environ. 90, 102615 https://doi.org/10.1016/j.trd.2020.102615 [Article].

Canepa, K., Hardman, S., Tal, G., 2019. An early look at plug-in electric vehicle adoption in disadvantaged communities in California. Transport Pol. 78, 19–30. https://doi.org/10.1016/j.tranpol.2019.03.009 [Article].

Cano, Z.P., Banham, D., Ye, S., Hintennach, A., Lu, J., Fowler, M., Chen, Z., 2018. Batteries and fuel cells for emerging electric vehicle markets. Nat. Energy 3 (4), 279–289. https://doi.org/10.1038/s41560-018-0108-1.

Chen, N., Akar, G., Gordon, S.I., Chen, S., 2020. Where do you live and what do you drive: built-environmental and spatial effects on vehicle type choice and vehicle use. International Journal of Sustainable Transportation 15 (6), 444–455. https://doi.org/10.1080/15568318.2020.1762950 [Article].

Contestabile, M., Tal, G., Turrentine, T., 2020. Who's Driving Electric Cars: Understanding Consumer Adoption and Use of Plug-In Electric Cars. Springer International Publishing. https://books.google.nl/books?id=3IAlzAEACAAJ.

Dieleman, F.M., Dijst, Martin, Burghouwt, G., 2002. Urban form and travel behaviour: micro-level household attributes and residential context. Urban Stud. 39 (33), 507–527. https://doi.org/10.1080/0042098022011280.

Eluru, N., Bhat, C.R., Pendyala, R.M., Konduri, K.C., 2010. A joint flexible econometric model system of household residential location and vehicle fleet composition/usage choices. Transportation 37 (4), 603–626. https://doi.org/10.1007/s11116-010-9271-3 [Article].

Erutku, C., 2020. A first look at ontario's electric vehicle incentive program: who are ontario's green drivers? Can. Publ. Pol. 46 (1), 37–44. https://doi.org/10.3138/cpp.2019-014 [Review].

Figenbaum, E., 2020. Norway—the world leader in BEV adoption. In: Contestabile, M., Tal, G., Turrentine, T. (Eds.), Who's Driving Electric Cars: Understanding Consumer Adoption and Use of Plug-In Electric Cars. Springer International Publishing, pp. 89–120. https://doi.org/10.1007/978-3-030-38382-4_6.

Fisher, M.J., Marshall, A.P., Mitchell, M., 2011. Testing differences in proportions. Aust. Crit. Care 24 (2), 133–138. https://doi.org/10.1016/j.aucc.2011.01.005.

Fornahl, D., Wernern, N., 2015. New electric mobility in fleets in the rural area of Bremen/Oldenburg. In: Leal Filho, W., Kotter, R. (Eds.), E-mobility in Europe: Trends and Good Practice. Springer International Publishing, pp. 237–251. https://doi.org/10.1007/978-3-319-13194-8_13.

Garikapati, V.M., Sidharthan, R., Pendyala, R.M., Bhat, C.R., 2014. Characterizing household vehicle fleet composition and count by type in integrated modeling framework. Transport. Res. Rec. 2429, 129–137. https://doi.org/10.3141/2429-14 [Review].

Gehrke, S.R., Reardon, T.G., 2021. Patterns and predictors of early electric vehicle adoption in Massachusetts [Article]. International Journal of Sustainable Transportation. https://doi.org/10.1080/15568318.2021.1912223.

Groot, C.d., Dam, F.v., Amsterdam, H.v., 2015. De stad: Magneet, roltrap en spons Bevolkingsontwikkelingen in stad en stadsgewest. https://www.pbl.nl/sites/default/files/downloads/PBL_2015_De_stad_magneet_roltrap_en_spons_1610_1.pdf.

Guerra, E., Cervero, R., Tischler, D., 2012. Half-mile circle. Transport. Res. Rec.: J. Transport. Res. Board 2276 (1), 101–109. https://doi.org/10.3141/2276-12.

Handelsblad, N., 2021. Electric driving is becoming more attractive, but 'subsidy is still desperately needed. https://www.nrc.nl/nieuws/2021/12/07/elektrisch-rijden-wordt-aantrekkelijker-maar-de-subsidie-blijft-hard-nodig-a4068118.

Hjorthol, R., 2013. Attitudes, ownership and use of electric vehicles- A review of literature. https://www.toi.no/getfile.php?mmfileid=32442.

IEA, 2022a. Global EV data explorer. https://www.iea.org/data-and-statistics/data-tools/global-ev-data-explorer.

IEA, 2022b. Transport. IEA. https://www.iea.org/reports/transport.

IenW, 2020. Subsidieregeling elektrisch rijden definitief; aanvragen vanaf 1 juli. https://www.nieuwsienw.nl/1679483.aspx.

Ioannides, D., Wall-Reinius, S., 2015. Sustainable mobility in the periphery: are electric vehicles the answer?. In: Charging Infrastructure for Electric Vehicles along the Green Highway Issue.

Jakobsson, N., Gnann, T., Plötz, P., Sprei, F., Karlsson, S., 2016. Are multi-car households better suited for battery electric vehicles? – Driving patterns and economics in Sweden and Germany [Article]. Transport. Res. C Emerg. Technol. 65, 1–15. https://doi.org/10.1016/j.trc.2016.01.018.

Jenn, A., Lee, J.H., Hardman, S., Tal, G., 2020. An in-depth examination of electric vehicle incentives: consumer heterogeneity and changing response over time. Transport. Res. Pol. Pract. 132, 97–109. https://doi.org/10.1016/j.tra.2019.11.004 [Article].

Joller, L., 2020. Who is embracing the short-term rental of electric cars? A case study on Estonia. Case Studies on Transport Policy 8 (3), 796–811. https://doi.org/10.1016/j.cstp.2020.06.003 [Article].

Kester, J., Sovacool, B.K., Noel, L., Zarazua de Rubens, G., 2020. Rethinking the spatiality of Nordic electric vehicles and their popularity in urban environments: moving beyond the city? J. Transport Geogr. 82, 102557 https://doi.org/10.1016/j.jtrangeo.2019.102557 [Article].

Khan, N.A., Habib, M.A., 2021. When do households make vehicle transactions? What type of vehicle households choose after transaction events? Travel Behaviour and Society 22, 32–47. https://doi.org/10.1016/j.tbs.2020.08.002 [Article].

Kitamura, R., Mokhtarian, P.L., Laidet, L., 1997. A micro-analysis of land use and travel in five neighborhoods in the San Francisco Bay Area. Transportation 25, 125–158.

Koetse, M.J., Hoen, A., 2014. Preferences for alternative fuel vehicles of company car drivers. Resour. Energy Econ. 37, 279–301. https://doi.org/10.1016/j.reseneeco.2013.12.006 [Article].

Lane, B.W., Dumortier, J., Carley, S., Siddiki, S., Clark-Sutton, K., Graham, J.D., 2018. All plug-in electric vehicles are not the same: predictors of preference for a plug-in hybrid versus a battery-electric vehicle. Transport. Res. Transport Environ. 65, 1–13. https://doi.org/10.1016/j.trd.2018.07.019.

Lee, J.H., Hardman, S.J., Tal, G., 2019. Who is buying electric vehicles in California? Characterising early adopter heterogeneity and forecasting market diffusion. Energy Res. Social Sci. 55, 218–226. https://doi.org/10.1016/j.erss.2019.05.011 [Article].

Liao, F., Molin, E., Timmermans, H., van Wee, B., 2018. The impact of business models on electric vehicle adoption: a latent transition analysis approach [Article]. Transport. Res. Pol. Pract. 116, 531–546. https://doi.org/10.1016/j.tra.2018.07.008.

Mandys, F., 2021. Electric vehicles and consumer choices. Renewable Sustainable Energy Rev. 142, 110874 https://doi.org/10.1016/j.rser.2021.110874 [Article].

Morton, C., Anable, J., Yeboah, G., Cottrill, C., 2018. The spatial pattern of demand in the early market for electric vehicles: evidence from the United Kingdom. J. Transport Geogr. 72, 119–130. https://doi.org/10.1016/j.jtrangeo.2018.08.020.

Mukherjee, S.C., Ryan, L., 2020. Factors influencing early battery electric vehicle adoption in Ireland. Renewable Sustainable Energy Rev. 118, 109504 https://doi.org/10.1016/j.rser.2021.110874 [Article].

NEA, 2021. Electric vehicles statistics in The Netherlands. https://doi.org/10.1016/j.rser.2021.110874.

NEA, 2022. Electric vehicles statistics in The Netherlands. https://doi.org/10.1016/j.rser.2021.110874.

Newman, D., Wells, P., Donovan, C., Nieuwenhuis, P., Davies, H., 2014. Urban, sub-urban or rural: where is the best place for electric vehicles? Int. J. Automot. Technol. Manag. 14, 306–323.

Oakil, A.T.M., Ettema, D., Arentze, T., Timmermans, H., 2013. Changing household car ownership level and life cycle events: an action in anticipation or an action on occurrence. Transportation 41 (4), 889–904. https://doi.org/10.1007/s11116-013-9507-0.

Olson, E.L., 2018. Lead market learning in the development and diffusion of electric vehicles. J. Clean. Prod. 172, 3279–3288. https://doi.org/10.1016/j.jclepro.2017.10.318 [Article].

Papaioannou, E.M., Hawkins, J., Habib, K.M.N., 2020. A study of car and home ownership decisions in the face of increasing commuting expenses (CHOICE) in the Greater Toronto Area (GTA) [Article]. Case Studies on Transport Policy 8 (3), 971–983. https://doi.org/10.1016/j.cstp.2020.04.009.

Peters, A., Dütschke, E., 2014. How do consumers perceive electric vehicles? A comparison of German consumer groups. J. Environ. Pol. Plann. 16 (3), 359–377. https://doi.org/10.1080/1523908X.2013.879037 [Article].

Peters, A.M., van der Werff, E., Steg, L., 2018. Beyond purchasing: electric vehicle adoption motivation and consistent sustainable energy behaviour in The Netherlands. Energy Res. Social Sci. 39, 234–247. https://doi.org/10.1016/j.erss.2017.10.008.

Pierre, M., Jemelin, C., Louvet, N., 2011. Driving an electric vehicle. A sociological analysis on pioneer users. Energy Efficiency 4 (4), 511–522. https://doi.org/10.1007/s12053-011-9123-9.

Plötz, P., Schneider, U., Globisch, J., Dütschke, E., 2014. Who will buy electric vehicles? Identifying early adopters in Germany. Transport. Res. Pol. Pract. 67, 96–109. https://doi.org/10.1016/j.tra.2014.06.006.

Qorbani, D., Korzilius, H.P.L.M., Fleten, S.-E., 2024. Ownership of battery electric vehicles is uneven in Norwegian households. Communications Earth & Environment 5 (1). https://doi.org/10.1038/s43247-024-01303-z.

Rith, M., Fillone, A., Biona, J.B.M., 2019. The impact of socioeconomic characteristics and land use patterns on household vehicle ownership and energy consumption in an urban area with insufficient public transport service - a case study of metro Manila. J. Transport Geogr. 79, 102484 [Article].

Rogers, E.M., 2003. Diffusion of Innovations, fifth ed. Simon and Schuster. ProQuest Ebook Central. https://ebookcentral.proquest.com.

Statista, 2021. Number of passenger cars sold in The Netherlands from 2010 to 2020. https://www.statista.com/statistics/423067/passenger-car-sales-in-the-netherlands/.

Tal, G., Nicholas, M.A., Woodjack, J., Scrivano, D., 2013. Who Is Buying Electric Cars in California Exploring Household and Vehicle Fleet Characteristics of New Plug-In Vehicle Owners.

Timmons, D., Perumal, A., 2016. US vehicle fuel-efficiency choices: demographic, behavioral, and cultural factors. J. Environ. Plann. Manag. 59 (12), 2179–2197. https://doi.org/10.1080/09640568.2015.1131675 [Article].

Vassileva, L., Campillo, J., 2017. Adoption barriers for electric vehicles: experiences from early adopters in Sweden. Energy 120, 632–641. https://doi.org/10.1016/j.energy.2016.11.119 [Article].

Wallbox, 2021. Everything you need to know about EV incentives in The Netherlands. https://blog.wallbox.com/netherlands-ev-incentives/.

Wang, N., Tang, L.H., Pan, H.Z., 2018. Analysis of public acceptance of electric vehicles: an empirical study in Shanghai. Technol. Forecast. Soc. Change 126, 284–291. https://doi.org/10.1016/j.techfore.2017.09.011.

White, L.V., Sintov, N.D., 2017. You are what you drive: environmentalist and social innovator symbolism drives electric vehicle adoption intentions. Transport. Res. Pol. Pract. 99, 94–113. https://doi.org/10.1016/j.tra.2017.03.008.

Wolbertus, R., van den Hoed, R., 2020. Plug-in (hybrid) electric vehicle adoption in The Netherlands: lessons learned. In: Contestabile, M., Tal, G., Turrentine, T. (Eds.), Who's Driving Electric Cars. Springer International Publishing, pp. 121–143. https://doi.org/10.1007/978-3-030-38382-4_7.

Yang, A., Liu, C., Yang, D., Lu, C., 2023. Electric vehicle adoption in a mature market: a case study of Norway. J. Transport Geogr. 106 https://doi.org/10.1016/j.jtrangeo.2022.103489.

Zhuge, C.X., Shao, C.F., 2019. Investigating the factors influencing the uptake of electric vehicles in Beijing, China: statistical and spatial perspectives. J. Clean. Prod. 213, 199–216. https://doi.org/10.1016/j.jclepro.2018.12.099.