Transportation Research Part A 192 (2025) 104325

Contents lists available at ScienceDirect

Transportation Research Part A

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

The effect of electric vehicle use on trip frequency and vehicle kilometers traveled (VKT) in the Netherlands

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ARTICLE INFO

Keywords:
Electric vehicles
Trip frequency
Vehicle kilometers traveled (VKT)
Commuting
Non-commuting
Ownership status
Range anxiety
Rebound effect

ABSTRACT

The transition from conventional vehicles to battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs) is expected to significantly contribute to reducing greenhouse gas emissions in the transportation sector. However, the effectiveness of this transition depends on how BEVs and PHEVs are used compared to internal combustion engine vehicles (ICEVs) and hybrid electric vehicles (HEVs). This paper analyzes data from the 2018–2020 Dutch National Travel Surveys to assess travel behavior of single-car households across four vehicle types: ICEVs, HEVs, PHEVs, and BEVs. Specifically, we focus on daily trip frequency and vehicle kilometers traveled (VKT) for both commuting and non-commuting purposes, while examining how these vehicle usage patterns correlate with vehicle attributes, socioeconomic and demographic factors, and the built environment. Our descriptive analysis shows that BEV and PHEV users have significantly longer daily VKT for both commuting and non-commuting travel compared to ICEV and HEV users. The model results reveal that after controlloing for various factors, BEVs are associated with shorter daily VKT for non-commuting travel compared to other powertrain types, while a pattern not observed for commuting travel. Notably, there is no evidence of a rebound effect linked to the use of BEV and PHEV powertrains. Additionally, leased or company vehicles, regardless of powertrain type, are associated with higher daily VKT and a higher probability of trip-making compared to privately owned vehicles. This higher daily VKT observed for BEV and PHEV users is largely due to the higher prevalence of their vehicles being leased or company cars, rather than the powertrain type itself.

1. Introduction

The transportation sector accounts for approximately one-quarter of global greenhouse gas (GHG) emissions (IEA, 2024), posing a significant challenge to efforts aimed at limiting global warming to below 1.5 °C. A key strategy for decarbonizing the transport sector is transitioning private car usage from internal combustion engine vehicles (ICEVs) to electric vehicles (EVs) (De Vos, 2024). This transition is expected to significantly reduce emissions, particularly when EVs are powered by clean, renewable energy sources (Cano et al., 2018). The main categories of EVs include hybrid electric vehicles (HEVs), plug-in hybrid electric vehicles (PHEVs), and battery electric vehicles (BEVs). Many countries have aggressively promoted the adoption of BEVs and PHEVs, with a strong emphasis on BEVs. For example, the Netherlands aims for all new passenger cars to be zero-emission by 2030, a target reflected in the increase in BEV sales from 0.8 % of new passenger car sales in 2015 to 21.3 % in 2022 (NEA, 2022). However, the long-term environmental

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https://doi.org/10.1016/j.tra.2024.104325
Received 9 October 2023; Received in revised form 1 November 2024; Accepted 11 November 2024
Available online 27 November 2024
0965-8564/

benefits of this transition depend not only on the number of BEVs and PHEVs adopted but also on their usage patterns —specifically, how frequently and how many kilometers these vehicles are driven compared to ICEVs and HEVs (Nunes et al., 2022). Understanding these usage patterns is essential to assess the true impact of BEVs and PHEVs on reducing emissions and advancing sustainable transport.

Existing research on BEV and PHEV usage has identified two main patterns related to trip frequency and vehicle kilometers traveled (VKT). First, BEVs are generally driven less often and for shorter distances due to their limited driving range compared to vehicles powered fully or partially by fossil fuels (Davis, 2019; Lane et al., 2018). This limitation often relegates BEVs to secondary vehicle status in multi-car households, alongside ICEVs. Second, the lower operating costs of BEVs and PHEVs may encourage more frequent use and longer driving distances (Langbroek et al., 2017). This "rebound effect" has the potential to offset the expected environmental benefits of BEV and PHEV adoption. Moreover, the increased use of these vehicles could exacerbate traffic congestion during peak hours.

However, it remains unclear whether the differences in BEV and PHEV usage patterns are inherently linked to the type of powertrain, possibly reflecting underlying factors such as range concern and operating costs, or whether they stem from other influences like socioeconomic and demographic characteristics (Chakraborty et al., 2022; Shin et al., 2019; Simsekoglu, 2018; Ye et al., 2018), the built environment (Boarnet & Crane, 2001; Choi, 2018; Julsrud, 2014; Nickkar et al., 2020), or vehicle attributes like ownership status (Huo et al., 2012; Ou et al., 2020; Weldon et al., 2016). BEV and PHEV users often differ from ICEV and HEV drivers in their characteristics (Chakraborty et al., 2022; Langbroek et al., 2017; Nickkar et al., 2020), which may explain the variations in usage patterns. Additionally, since BEVs and PHEVs in the Netherlands (our study area) are predominantly acquired through leasing schemes (Liao et al., 2019), ownership status might significantly influence how these vehicles are used. Thus, to fully understand the impact of rising BEV and PHEV adoption on travel behavior, it is essential to determine whether these differences in usage are due to the powertrain itself or the characteristics of the users.

To avoid biases introduced by substitution effects between vehicles in multi-car households (Davis, 2023; Hasan & Simsekoglu, 2020), this study focuses on vehicle usage in single-car households. Notably, single-car households account for a significant share (56.91 %) of all car-owning households in the Netherlands, the focus area of this study. By narrowing the scope, we can more accurately analyze the usage patterns of BEVs and PHEVs compared to ICEVs and HEVs, assessing their potential to replace conventional vehicles in situations where only one car is available.

In addition, previous studies on BEV and PHEV usage have primarily focused on trip frequency and VKT, often overlooking the purpose of trips (Burlig et al., 2021; Davis, 2019; Langbroek et al., 2017; Nickkar et al., 2020; Niklas et al., 2020; Shin et al., 2019; Simsekoglu, 2018). However, to evaluate whether BEVs and PHEVs can effectively meet daily travel needs and serve as viable alternatives to ICEVs and HEVs, it is essential to analyze usage patterns based on travel purpose, specifically distinguishing between commuting and non-commuting trips. Commuting trips are typically regular and predictable, making it easier to plan energy consumption and charging at reliable locations like home or work. In contrast, non-commuting trips are more variable in distance, less predictable, and more uncertain regarding charging availability. These differences can impact battery range management and raise concerns about charging availability, which may lead to different usage patterns across vehicle types. For example, while BEV and PHEV drivers may feel confident during their routine commutes, they might hesitate to undertake non-commuting trips due to concerns about range and access to charging stations.

To address the identified research gaps, this study analyzes data from national travel surveys conducted over three years (2018–2020) to explore the following research questions:

- How do the usage patterns of BEVs and PHEVs differ from those of ICEVs and HEVs in terms of daily trip frequency and VKT? How do these patterns vary between commuting and non-commuting purposes?
- How do socioeconomic and demographic factors, built environment, and vehicle attributes correlate with vehicle usage patterns?
- Are differences in usage patterns between powertrain types associated with the powertrain itself, or are they linked to other factors? Exploring this relationship can shed light on the potential roles of range anxiety and operating costs in shaping BEV and PHEV usage.

This study is critical from both a societal perspective, such as meeting daily mobility needs, and a transportation perspective, particularly in managing congestion. It explores the potential of BEVs and PHEVs as viable alternatives to ICEVs within the broader transition to electric mobility. By analyzing vehicle usage patterns, the findings could guide policy and planning efforts to foster a more sustainable and efficient transportation system.

2. Literature review

This section presents a review of existing literature on the correlations between socioeconomic and demographic characteristics, built environment attributes, and vehicle attributes with vehicle usage patterns, with a particular focus on trip frequency and distance traveled. In this study, distance traveled is referred to as VKT, though it is sometimes referred to as vehicle mileage traveled (VMT) in other contexts.

2.1. Effect of socioeconomic and demographic characteristics on vehicle usage

Previous studies have shown that socioeconomic and demographic characteristics—such as gender, age, education, income, and household composition—significantly influence the usage patterns of ICEVs and HEVs (Abdullah et al., 2021; Akar & Guldmann, 2012; Boarnet & Crane, 2001; Dieleman et al., 2002; Ye et al., 2018). As PHEVs and BEVs have become more prevalent in household vehicle ownership, these same characteristics have been shown to similarly affect the usage patterns of BEVs and PHEVs, as confirmed by Nickkar et al. (2020) and Chakraborty et al. (2022). However, the magnitude of these effects may differ when comparing BEVs and PHEVs with ICEVs and HEVs.

For example, men tend to be the primary users of cars across most households, including ICEVs, HEVs, and plug-in electric vehicles (PEVs) (Akar & Guldmann, 2012; Farkas et al., 2018; Havet et al., 2021; IEA, 2018; Julsrud, 2014), where PHEVs and BEVs are grouped as PEVs. Younger drivers, individuals in households with more children and vehicles, households with a higher proportion of workers, and those with longer commutes are more likely to frequently use ICEVs, HEVs, and PEVs, resulting in higher VKT (Akar & Guldmann, 2012; Boarnet & Crane, 2001; Figenbaum & Kolbenstvedt, 2016).

Chakraborty et al. (2022) found a positive correlation between household size and total household VKT across all powertrain types, as families with children tend to use vehicles more frequently, particularly for non-commuting trips, leading to higher VKT (Boarnet & Crane, 2001; Dieleman et al., 2002; Figenbaum & Kolbenstvedt, 2016; Ye et al., 2018). PEV users, compared to ICEV and HEV users, are generally more highly educated, wealthier, and tend to make significantly more trips, driving a greater share of the total daily travel distance (Langbroek et al., 2017). In multi-car households, an increase in the number of drivers is associated with a higher proportion of PEV VKT relative to ICEV VKT in the total household VKT (Chakraborty et al., 2022).

Additionally, awareness of environmental sustainability influences vehicle usage patterns. Andersson et al. (2019) found that households purchasing fuel-efficient cars for environmental reasons are less likely to experience the rebound effect typically associated with increased fuel efficiency, compared to those buying standard ICEVs without environmental motivations. Similarly, Farkas et al. (2018) observed in the U.S. that PEV drivers with environmental concerns tend to drive shorter distances when traveling between counties, cities, and out-of-state, in contrast to those without such concerns.

2.2. Effect of the built environment on vehicle usage

The built environment has a significant influence on vehicle usage patterns. Research on ICEVs and HEVs shows that car dependency tends to be lower in urban environments compared to suburban and rural areas. Urban areas, characterized by high density, diverse services, and extensive public transportation options, offer greater accessibility for walking and cycling (Boarnet & Crane, 2001; Dieleman et al., 2002). Consequently, households in urban areas with higher walkability indices typically have lower VKT (Akar & Guldmann, 2012; Chakraborty et al., 2022; Figueroa et al., 2014). The concentration of employment opportunities in city centers also reduces car usage in urban areas. For example, in Calgary, Canada, over half of the city's jobs are located downtown, leading to significantly higher VKT for households in suburban and rural areas (Choi, 2018). Furthermore, Kim and Brownstone (2013) found that relocating a household from a suburban area to an urban one could reduce annual household VKT by as much as 18 %.

2.3. Effect of vehicle attributes on vehicle usage

Previous research has shown that socioeconomic and demographic characteristics, as well as the built environment, influence vehicle usage patterns, with variations observed across BEVs, PHEVs, HEVs, and ICEVs. In addition to these factors, vehicle attributes—such as powertrain type, ownership status, and the availability of other cars in a household—also play a significant role in shaping usage patterns, as discussed below.

2.4. Effect of powertrain types on vehicle usage

The type of powertrain plays a significant role in car usage, affecting both operating costs per kilometer and perceived range. For ICEVs and HEVs, operating costs—often measured by fuel costs and fuel economy—are significant factors. Higher fuel prices and stricter fuel economy standards tend to reduce fuel consumption, though they do not necessarily impact VKT (Steren et al., 2022). However, high fuel prices can incentivize households to switch to more fuel-efficient, lower-emission vehicles (Catherine & Alejandra, 2019; De Borger et al., 2016). This shift may lead to an increase in VKT, thereby offsetting the expected fuel savings, a phenomenon known as the rebound effect (Gillingham, 2018; Linn, 2016).

BEV and PHEV usage is often shaped by range limitations and the associated range anxiety—the fear of running out of battery mid-journey. This concern can discourage drivers from using BEVs and PHEVs for longer trips or frequent travel. Studies in Ireland (Weldon et al., 2016), Norway (Figenbaum & Kolbenstvedt, 2016), the U.S. (Burlig et al., 2021; Davis, 2019), and Germany (Habla et al., 2021) have all noted this effect. For example, Weldon et al. (2016) found that, between 2011 and 2014 in Ireland, BEVs were primarily used for shorter trips compared to ICEVs. Similarly, Davis (2019) analyzed 2017 U.S. National Household Travel Survey (NHTS) data and found that BEVs and PHEVs are driven significantly fewer miles per year than ICEVs and HEVs, with BEVs recording the lowest annual household VKT in California. In Germany, Habla et al. (2021) observed that BEVs were driven shorter distances on average than ICEVs, both annually and for single-day trips, based on data from 2016 to 2017. Comparisons of PHEV and BEV usage show that BEVs typically have lower household VKT in single-car households and account for a smaller share of total household VKT in multi-car households (Chakraborty et al., 2022; Davis, 2019). These differences are likely due to PHEVs' dual power sources—battery and fossil fuel—which offer greater flexibility and alleviate range anxiety, making PHEVs more suitable for longer trips compared to BEVs.

Range anxiety can lead people to perceive that BEVs and PHEVs, particularly BEVs, are less suitable for irregular or long trips, often relegating them to a secondary role in households rather than fully replacing ICEVs. For instance, in Norway, BEVs are primarily used for longer weekday commutes but are less frequently chosen for vacation travel (Figenbaum & Kolbenstvedt, 2016). Similarly, Chakraborty et al. (2022) found that BEVs and PHEVs are driven more frequently for commuting than for other purposes. Niklas et al. (2020) noted that in both Germany and California, BEVs are not yet exclusively relied upon for everyday mobility as ICEVs are. However, they also observed that BEVs are increasingly used for single long-distance trips, likely due to technological advancements extending their electric driving range. Supporting this, Chakraborty et al. (2022) reported that owners of long-range BEVs are more inclined to use their vehicles not only for long commutes but also for weekend trips. Additionally, several studies have shown that the current driving range of PHEVs and BEVs meets the majority of daily travel needs in terms of VKT. This has been observed in the U.S. (Du et al., 2013), China (Ou et al., 2020), Finland and Switzerland (Melliger et al., 2018), as well as six European countries: Germany, Spain, France, Italy, Poland, and the UK (Pasaoglu et al., 2014).

BEVs and PHEVs typically have lower operating costs compared to ICEVs and HEVs, which may lead to increased car usage. In some instances, these cost advantages lead to greater reliance on cars, even replacing trips that would otherwise be made by walking, cycling, or using public transport—a phenomenon known as the rebound effect. For example, in Greater Stockholm, Langbroek et al. (2017) analyzed revealed preference (RP) data from late 2014 and found that PEV users tend to make more trips than non-PEV users, and PEVs account for a larger share of their daily VKT compared to ICEVs. Additionally, using stated preference (SP) data from 2014 to 2015, Langbroek et al. (2018) found that PEV users are more likely to increase their trips on weekends and for chained activities such as shopping and leisure. Similarly, Simsekoglu (2018) analyzed data from Norway in 2016 and found that BEV owners drive more frequently and walk less than ICEV drivers. These findings highlight that the impact of PHEV and BEV usage on overall travel behavior may vary depending on the specific context.

2.5. Effect of ownership status, age, and size on vehicle usage

The ownership status of a vehicle—whether it is owned or leased—significantly influences vehicle usage patterns. Privately leased cars tend to be driven more frequently than owned cars, as users seek to maximize the value of their lease. Company cars, on the other hand, are often used more extensively for commuting, as seen in the Netherlands (Dutch Tax and Customs Administration Belastingdienst, 2022). For example, Weldon et al. (2016) found that business-leased BEVs were used for a higher number of short weekday trips compared to privately owned BEVs. In the U.S., Chakraborty et al. (2022) observed that during the summer, purchased PEVs accounted for a larger share of non-commuting trips within households compared to leased PEVs, where penalties or additional fees may be incurred for exceeding mileage limits. However, the influence of ownership status on EV usage patterns remains underexplored in the literature.

VKT is closely linked to a vehicle's price, age, and size. Larger and more expensive vehicles typically have higher annual VKT, as vehicle price often correlates with size (Ou et al., 2020). Newer vehicles are generally driven more intensively, with higher annual VKT observed in newer models compared to older ones (Huo et al., 2012; Ou et al., 2020). This trend may be especially pronounced for BEVs and PHEVs, where technological advancements, such as extended driving ranges in newer models, likely contribute to greater differences in VKT between newer and older vehicles.

2.6. Effect of other cars in the household on vehicle usage

Most BEV and PHEV consumers belong to multi-car households, as seen in the U.S. (Raghavan & Tal, 2021), Sweden and Germany (Jakobsson et al., 2016), Norway (IEA, 2018), and the Netherlands (Zhang et al., 2024). In these households, the usage of BEVs or PHEVs is shaped by the performance and characteristics of other vehicles, typically ICEVs. Haugneland et al. (2016) found that in Norway, PEVs are frequently the most used vehicles in multi-car households, particularly for everyday commuting (95 %) and common day trips (57 %). Moreover, in Nordic countries, multi-car households with both a PEV and an ICEV often prefer the PEV for long journeys (IEA, 2018). Chakraborty et al. (2022) observed that in multi-car households, PEVs may account for a smaller share of total household VKT compared to other vehicles, especially if the PEV has limited range. Conversely, when the other vehicles in the household are less fuel-efficient, costlier to operate, or older than the PEV, the share of PEV VKT tends to be higher. This indicates that BEVs and PHEVs in multi-car households are generally used for regular trips, where drivers can manage their travel needs within the vehicle's electric range. In contrast, single-car households lack the flexibility to substitute vehicles, which significantly influences PEV usage patterns. To avoid biases related to the presence of other vehicles, this paper focuses specifically on vehicle usage patterns within single-car households.

2.7. Conceptual model for vehicle usage patterns

Previous studies suggest that BEVs and PHEVs may be used differently from ICEVs and HEVs in terms of trip frequency and VKT. Some research indicates that BEVs and PHEVs lead to increased car usage, while other studies suggest the opposite. However, it remains unclear whether these differences are inherently due to the powertrain type or influenced by other factors. BEV and PHEV users often differ from ICEV and HEV users in terms of socioeconomic and demographic characteristics, built environments, and vehicle ownership status. Additionally, the distinction between commuting and non-commuting travel is critical for understanding BEV and PHEV usage patterns, yet this aspect has rarely been explored.

Building on existing literature, this paper examines how socioeconomic and demographic characteristics, the built environment, and vehicle attributes correlate with the usage patterns of different powertrain types, including ICEVs, HEVs, PHEVs, and BEVs. The study focuses on trip frequency and daily VKT, differentiating between commuting and non-commuting purposes. The conceptual model for this analysis is presented in Fig. 1.

3. Data and methods

3.1. Study context

The Netherlands has set a clear policy goal to ensure that by 2030, only zero-emission vehicles will be sold as new cars. Supported by subsidies and tax incentives, this policy has led to a significant increase in BEV sales, from 0.8 % of new passenger car sales in 2015 to 21.3 % in 2022 (NEA, 2022). This study utilizes data from the Dutch National Travel Survey (DNTS, Onderzoek Onderweg in Dutch), provided by Statistics Netherlands (CBS). The DNTS captures the travel patterns of a nationally representative sample of the Dutch population through one-day travel diaries. It also gathers detailed information on socioeconomic and demographic characteristics, residential environment, and trip specifics, including trip length, transport mode, and purpose. Crucially, the DNTS enables the identification of household car ownership, car fuel types, and residential locations down to the first four digits of postal codes (PC4), which aggregate several six-digit postal code areas.

The 2018–2020 DNTS included data from 173,580 households. 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. The cars could be owned, leased, or company vehicles. In the DNTS, "privately leased car" and "company car" are combined into a single category termed "leased/company car". For consistency, this paper uses "leased or company car" to collectively refer to both. Single-car households made up the largest share of Dutch households with at least one car (56.91 %), and due to data availability, this study focuses exclusively on single-car households. Respondents under 18 years of age were excluded, as only individuals aged 18 or older can legally hold a driver's license in the Netherlands. To increase the sample size, particularly for BEV and PHEV users, we combined data from 2018 and 2019. To explore developments in the BEV and PHEV market, we compared this combined data with data from 2020. After removing observations with missing values, the final sample included 67,506 households.

3.2. Data collection and indicators

3.2.1. Sample segmentation

We categorized individuals based on the type of vehicle used within their household, distinguishing between ICEVs, HEVs, PHEVs, and BEVs, listed in order of increasing electrification. To analyze vehicle usage patterns, we employed three key indicators: daily VKT, which measures the total distance driven per person per day; the number of trips, reflecting how often a person uses the car each day; and travel purposes, categorized as commuting or non-commuting. Commuting trips refer to travel to and from work, while non-commuting trips encompass activities such as recreation, shopping, and visiting friends or relatives. Only trips where the individual was the driver were included in the analysis, while commuting trips were limited to employed individuals.

3.2.2. Explanatory variables

Guided by existing literature and constrained by the available data, this study employs a variety of explanatory variables to analyze vehicle usage patterns. These variables include socioeconomic and demographic factors, built environment characteristics, and vehicle

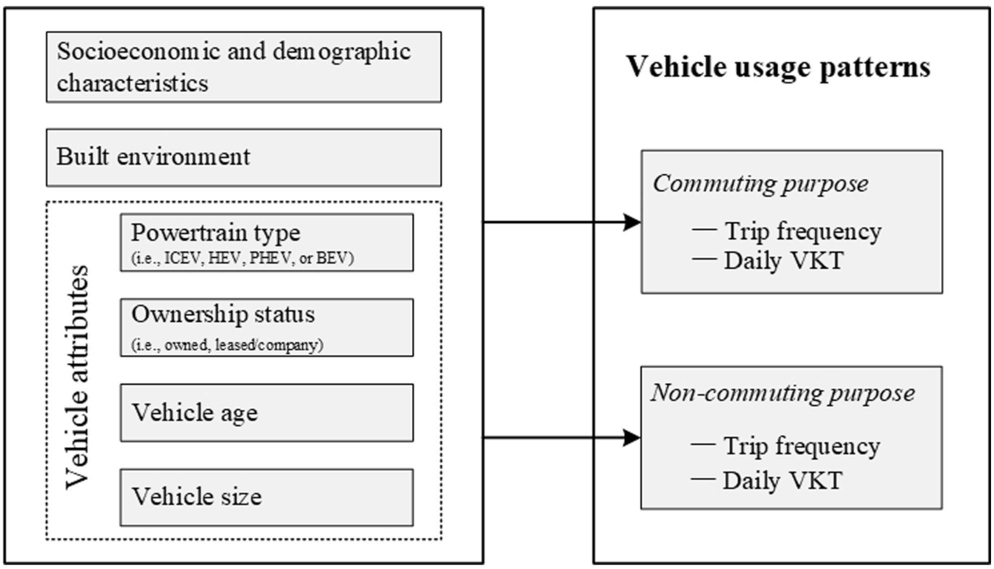

Fig. 1. Conceptual model.

attributes (see Table 3).

Socioeconomic and demographic characteristics encompass several factors. Gender is categorized as female or male, while age is divided into six groups: 18–29 years, 30–39 years, 40–49 years, 50–59 years, 60–69 years, and 70 years and older. Education levels are classified into three categories: 1) low, including no completed training, primary education, and lower vocational education; 2) moderate, including secondary vocational education; and 3) high, including higher vocational education and university degrees. Work status and weekly hours are grouped as no paid work, up to 12 h, 12–30 h, and 30 or more hours. Households are categorized by the number of adults over 18: 1 adult, 2 adults, or 3 or more adults. The number of children under 6 is classified as none, 1, or 2 or more, while the number of older children (aged 6 to 17) is similarly categorized as none, 1, or 2 or more. Households are also grouped by the number of driving licenses they hold: 1, 2, or 3 or more. Finally, household disposable income is divided into five quintiles, ranging from the lowest (first quintile) to the highest (fifth quintile).

The built environment attributes in this study include several factors. The degree of urbanization is determined by the density of addresses at the PC4 level and is categorized into four groups: extremely urbanized (2,500 or more addresses per km^2), highly urbanized (1,500–2,000 addresses per km^2), moderately urbanized (1,000–1,500 addresses per km^2), and barely or not urbanized (fewer than 1,000 addresses per km^2). The availability of supermarkets and grocery stores is measured by the average number of these facilities within a one-kilometer road distance for all residents in a given PC4 area. Walkability is defined by the presence of at least one train station within one kilometer of all residents in a PC4 area, coded as 1 if a station is within this distance, and 0 otherwise. Cycling accessibility is measured by the presence of a train station within 1 to 4 km of all residents in the area.

Vehicle attributes considered in this study include the type, ownership status, age, and weight of the car. Powertrain types are categorized as ICEV, HEV, PHEV, and BEV. Ownership status is divided into two groups: owned cars and leased/company cars. Car age is classified into five brackets: 0–1 year, 2–4 years, 5–9 years, 10–15 years, and over 15 years. Vehicle weight, used as a proxy for size, is grouped into five categories: under 951 kg, 951–1,150 kg, 1,151–1,350 kg, 1,351–1,550 kg, and over 1,550 kg.

3.2.3. Statistical approaches

This study employed descriptive statistics to summarize the characteristics of car users and their usage patterns. To examine differences in travel behavior—specifically daily trip frequency, daily VKT, and VKT per trip, stratified by travel purpose—among users of different powertrain types, we conducted a one-way analysis of variance (ANOVA). The ANOVA and F-distribution statistics were used to compare the mean travel behavior across four independent groups (as shown in Table 2). The null hypothesis assumed that the means of these indicators are the same across all groups, while the alternative hypothesis posited that at least one group has a significantly different mean. The significance of the ANOVA tests was evaluated at a 95 % confidence interval (CI).

For the regression analyses, we focused on daily trip frequency and daily VKT, with these metrics stratified by commuting and non-commuting trips as the dependent variables. A significant portion of respondents reported no car trips (80.65 % for commuting trips and 71.96 % for non-commuting trips), resulting in a high number of zero values in the data. To address this, we applied hurdle and Tobit models, which are well-suited for handling data with an excess of zero values by censoring these cases when no car trips were made. Specifically, we used two hurdle regression models to analyze the number of trips, stratified by commuting and non-commuting, and two Tobit regression models to assess daily VKT, also stratified by these purposes. All analyses were conducted using R.

4. Results

4.1. Descriptive results

Table 1 presents the descriptive statistics for socioeconomic, demographic, and built environment characteristics for the study population from 2018 to 2020. In our sample, 95.46 % of single-car households were ICEV users. There were notable differences among ICEV, HEV, PHEV, and BEV users in terms of car ownership status, work status and hours, educational level, household income, and degree of urbanization. Most ICEVs and HEVs were owned (94.18 % and 92.45 %, respectively), while the majority of BEVs and PHEVs were leased or company cars (81.50 % and 55.91 %, respectively). BEV and PHEV users tend to have higher incomes and education levels compared to ICEV and HEV users. BEV and PHEV users were more likely to work longer hours compared to ICEV and HEV users and were more likely to live in highly urbanized areas (50 % and 37.27 %, respectively).

Table 2 presents trip frequency and VKT, distinguishing between commuting and non-commuting purposes, among users of different vehicle types (ICEVs, HEVs, PHEVs, and BEVs) from 2018 to 2020. The ANOVA test results reveal significant differences in both daily VKT and VKT per trip for commuting and non-commuting travel among these vehicle user groups. However, no significant differences were found in daily trip frequency for either commuting or non-commuting purposes across these groups.

Regardless of travel purpose, BEV and PHEV users reported higher average daily VKT compared to ICEV and HEV users. Specifically, BEV and PHEV users averaged 25.35 km and 26.77 km per day, respectively, when including those who did not make car trips, and 65.44 km and 70.11 km, respectively, when excluding them. In contrast, ICEV and HEV users averaged 15.90 km and 17.18 km per day, respectively, including those who did not make car trips, and 47.05 km and 50.64 km, respectively, when excluding them. Similarly, BEV and PHEV users recorded longer average VKT per trip, at 26.68 km and 28.73 km, respectively, compared to ICEV and HEV users, who averaged 20.22 km and 22.13 km per trip. In terms of daily trip frequency, BEV and PHEV users did not differ significantly from ICEV and HEV users, with BEV users averaging 3.04 trips per day, PHEV users 2.83 trips, ICEV users 2.74 trips, and HEV users 2.71 trips.

Table 1
Descriptive statistics of socioeconomic, demographic and built environment characteristics of the study population (2018–2020 pooled data).

		Car users		ICEV users		HEV users		PHEV users		BEV users	
Travel purpose (Total [T], Commuting [C], Non-commuting [NC])		T/NC	C	T/NC	C	T/NC	C	T/NC	C	T/NC	C
		% per category	% per category	% per category	% per category	% per category	% per category	% per category	% per category	% per category	% per category
Sample size		67,506	35,405	64,442	33,699	2,278	1,094	440	331	346	281
Powertrain type	ICEV	95.46	95.18	100	100	0	0	0	0	0	0
	HEV	3.37	3.09	0	0	100	100	0	0	0	0
	PHEV	0.65	0.93	0	0	0	0	100	100	0	0
	BEV	0.51	0.79	0	0	0	0	0	0	100	100
Vehicle year	2018–2019	63.57	64.06	64.04	64.60	57.20	59.14	54.55	56.50	30.06	26.69
	2020	36.43	35.94	35.96	35.40	42.80	40.86	45.45	43.50	69.94	73.31
Ownership status	Owned	93.41	89.62	94.18	90.87	92.45	86.47	44.09	38.07	18.50	12.81
	Leased/company	6.59	10.38	5.82	9.13	7.55	13.53	55.91	61.93	81.50	87.19
Vehicle age (years)	0–1	5.80	6.04	5.18	5.35	13.35	10.51	6.62	5.17	70.55	72.66
	2–4	15.74	15.38	15.11	14.73	26.73	23.86	44.98	48.02	24.20	21.94
	5–9	31.82	32.43	31.44	32.03	43.77	47.26	47.49	45.90	5.25	5.40
	10–15	31.06	31.15	31.96	32.13	16.07	18.19	0.46	0.30	0.00	0.00
	>15	15.58	15.01	16.32	15.76	0.09	0.18	0.46	0.61	0.00	0.00
Vehicle weight (kg)	<951	10.87	11.01	11.33	11.51	1.41	1.19	0.00	0.00	0.95	0.78
	951–1150	23.98	23.18	25.03	24.30	2.03	1.01	0.25	0.00	0.63	0.78
	1151–1350	29.46	29.06	29.92	29.85	25.30	19.03	0.74	0.32	3.49	3.88
	1351–1550	25.65	25.62	24.54	24.51	61.48	68.29	10.81	9.39	10.16	8.14
	>1550	10.04	11.13	9.18	9.83	9.78	10.48	88.21	90.29	84.76	86.43
Gender	Male	51.40	52.91	51.26	52.73	53.12	54.02	57.50	61.03	59.25	60.14
	Female	48.60	47.09	48.74	47.27	46.88	45.98	42.50	38.97	40.75	39.86
Age (years)	18–29	12.61	15.99	12.74	16.19	7.99	11.06	11.36	9.97	19.08	17.79
	30–39	14.13	23.81	14.04	23.72	13.30	24.04	20.23	23.56	28.61	33.45
	40–-49	14.66	23.99	14.57	23.88	13.61	25.05	27.05	31.12	21.97	24.20
	50–59	15.33	23.34	15.35	23.37	13.43	23.67	20.45	23.26	17.92	19.22
	60–69	18.80	11.88	18.75	11.85	22.70	14.99	14.32	10.27	8.09	4.98
	70 or above	24.48	1.00	24.55	0.99	28.97	1.19	6.59	1.81	4.34	0.36
Education level	Low	27.92	13.79	28.39	14.13	22.30	9.23	7.05	4.23	4.62	2.14
	Moderate	31.33	34.04	31.67	34.64	24.50	23.40	26.59	24.77	18.79	15.30
	High	40.75	52.16	39.94	51.23	53.20	67.37	66.36	71.00	76.59	82.56
Work status and weekly hours (#)	No paid work	47.55	–	47.71	–	51.98	–	24.77	–	18.79	–
	≤12	2.76	5.27	2.77	5.29	2.81	5.85	1.82	2.42	3.18	3.91
	12–30	12.35	23.54	12.41	23.74	10.76	22.39	15.45	20.54	6.65	8.19
	≥30	37.34	71.19	37.11	70.97	34.46	71.76	57.95	77.04	71.39	87.90
Adults (#)	1	22.08	24.47	22.32	24.76	16.29	18.10	17.73	19.03	21.97	21.35
	2	65.84	61.80	65.54	61.43	73.31	68.65	69.32	69.49	68.50	70.46
	≥3	12.07	13.73	12.14	13.81	10.40	13.25	12.95	11.48	9.54	8.19
Young children (#)	0	90.59	84.74	90.68	84.86	89.90	81.90	85.00	81.87	85.26	83.99
	1	6.32	10.22	6.27	10.15	6.67	11.79	9.09	10.57	9.83	11.39
	≥2	3.09	5.04	3.05	4.98	3.42	6.31	5.91	7.55	4.91	4.63
Older children (#)	0	82.02	72.84	82.02	72.81	84.37	73.95	72.95	71.00	77.17	74.73
	1	9.10	13.36	9.12	13.44	8.17	12.89	9.32	9.06	10.12	11.03
	≥2	8.89	13.79	8.86	13.75	7.46	13.16	17.73	19.94	12.72	14.23
Drivers licenses (#)	1	38.87	36.54	39.24	36.83	31.71	31.43	27.48	29.88	31.27	30.32
	2	55.00	56.07	54.62	55.78	62.28	60.46	65.59	63.72	64.60	65.34

(continued on next page)

Table 1 (*continued*)

		Car users		ICEV users		HEV users		PHEV users		BEV users	
	≥3	6.13	7.38	6.14	7.39	6.01	8.11	6.93	6.40	4.13	4.33
Household income level (quintile)	First	10.41	7.17	10.61	7.33	6.50	4.66	4.32	3.02	5.78	3.20
	Second	21.79	14.60	22.24	14.95	14.57	9.14	7.05	6.04	4.05	3.20
	Third	21.67	21.19	21.92	21.57	18.53	15.90	11.59	10.57	8.67	8.54
	Fourth	23.58	26.84	23.54	27.03	26.91	25.59	16.36	16.31	19.65	21.00
	Fifth	22.54	30.20	21.69	29.11	33.49	44.70	60.68	64.05	61.85	64.06
Urbanization degree	Barely or not urbanized	25.87	22.67	26.16	23.03	20.98	16.54	19.77	17.52	11.85	10.32
	Moderate	16.34	15.27	16.39	15.35	16.24	14.08	14.09	13.29	11.85	12.10
	Strong	32.02	31.69	32.01	31.79	33.71	32.18	28.86	27.49	26.30	23.13
	Extreme	25.77	30.36	25.45	29.83	29.06	37.20	37.27	41.69	50.00	54.45
Walkability of train stations	No	91.84	90.71	91.87	90.80	92.01	89.31	89.55	89.73	86.99	86.83
	Yes	8.16	9.29	8.13	9.20	7.99	10.69	10.45	10.27	13.01	13.17
Cycling accessibility of train stations	No	44.20	42.05	44.36	42.26	42.05	39.21	37.73	33.84	37.86	37.37
	Yes	55.80	57.95	55.64	57.74	57.95	60.79	62.27	66.16	62.14	62.63
		Avg. (SD.)	Avg. (SD.)	Avg. (SD.)	Avg. (SD.)	Avg. (SD.)	Avg. (SD.)	Avg. (SD.)	Avg. (SD.)	Avg. (SD.)	Avg. (SD.)
Supermarkets and grocery stores (#)		10.90 (14.52)	12.27 (16.30)	10.87 (14.49)	12.21 (16.25)	10.31 (13.53)	12.15 (15.75)	13.70 (17.36)	14.36 (17.89)	16.38 (19.71)	17.73 (20.89)

Table 2
Usage patterns of ICEVs, HEVs, PHEVs, and BEVs (2018–2020 pooled data).

		Carusers			ICEVusers			HEVusers			PHEVusers			BEVusers		
Travel purpose (Total [T], Commuting [C], Non-commuting [NC])		T	C	NC	T	C	NC	T	C	NC	T	C	NC	T	C	NC
Sample size		67,506	35,405	67,506	64,442	33,699	64,442	2,278	1,094	2,278	440	331	440	346	281	346
		% per category	% per category	% per category	% per category	% per category	% per category	% per category	% per category	% per category	% per category	% per category	% per category	% per category	% per category	% per category
Car trip frequency (#)	0	66.16	80.65	71.96	66.21	80.60	72.02	66.07	83.00	70.90	61.82	79.76	69.09	61.27	78.65	70.52
	1	3.27	5.05	3.69	3.27	5.07	3.68	3.51	3.75	3.95	2.73	5.74	3.41	2.31	6.76	2.89
	2	17.66	13.09	14.51	17.63	13.13	14.48	17.95	12.07	15.06	18.86	12.39	16.82	18.50	13.52	13.87
	3	4.70	0.75	3.66	4.69	0.73	3.66	4.39	1.01	3.51	6.82	1.81	5.45	5.20	0.71	3.47
	4	4.75	0.40	3.49	4.75	0.42	3.49	4.35	0.09	3.51	5.00	0.00	2.27	7.23	0.36	5.20
	5	1.57	0.03	1.18	1.55	0.03	1.16	1.89	0.00	1.58	3.18	0.30	2.05	2.60	0.00	1.73
	≥6	1.89	0.03	1.52	1.89	0.02	1.52	1.84	0.09	1.49	1.59	0.00	0.91	2.89	0.00	2.31
		N	N	N	N	N	N	N	N	N	N	N	N	N	N	N
Trip frequency (Avg. #, incl. no car trips)		0.93	0.35	0.74	0.92	0.35	0.74	0.92	0.32	0.77	1.08	0.37	0.80	1.18	0.37	0.87
Trip frequency (Avg. #, excl. no car trips)		2.74	1.83	2.64	2.74	1.83	2.64	2.71	1.88	2.63	2.83	1.85	2.58	3.04	1.75	2.96
		km	km	km	km	km	km	km	km	km	km	km	km	km	km	km
VKT (Daily, incl. no car trips)	Avg.	16.06	8.75	11.47	15.90	8.66	11.37	17.18	8.58	13.06	26.77	13.34	16.73	25.35	14.37	13.67
	SD.	40.25	27.16	34.83	39.9	26.83	34.58	43.03	26.72	38.58	59.04	42.58	46.38	51.55	40.84	36.59
VKT (Daily, excl. no car trips)	Avg.	47.45	45.21	40.91	47.05	44.65	40.63	50.64	50.48	44.88	70.11	65.9	54.14	65.44	67.32	46.37
	SD.	57.42	46.52	55.88	56.98	45.87	55.55	61.36	45.74	60.74	78.14	74.5	70.39	65.18	65.49	55.15
VKT (Per trip, excl. no car trips)	Avg.	20.39	24.81	18.54	20.22	24.54	18.41	22.13	60.54	55.90	28.73	34.40	24.57	26.68	38.21	18.75
	SD.	28.52	23.90	29.40	28.37	23.62	29.29	29.59	56.97	83.13	35.54	34.60	35.03	33.17	34.13	29.20
			C F (Sig.)	NC F (Sig.)												
ANOVA tests	Trip frequency (#, incl. no car trips)		0.86	1.49												
	VKT (Daily, incl. no car trips)		7.31 ***	5.58 ***												
	Trip frequency (#, excl. no car trips)		0.77	1.66												
	VKT (Daily, excl. no car trips)		10.09 ***	4.13 **												
	VKT (Per trip, excl. no car trips)		129.36 ***	280.29 ***												

Signif. codes: 0 “***” 0.001 “**” 0.01 “*” 0.05 “.” 0.1 “” 1

Table 3
Hurdle model results for car trip frequency by commuting and non-commuting purposes.

		Commuting				Non-commuting			
		Zero hurdle		Count hurdle		Zero hurdle		Count hurdle	
Variable		Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.
(Intercept)		−1.613	***	0.344	**	−1.009	***	0.766	***
Year	2018–2019 (ref.)								
	2020	−0.438	***	−0.075	**	−0.240	***	0.004	
Ownership status	Owned (ref.)								
	Leased/company	0.366	***	−0.002		0.239	***	0.021	
Powertrain type	ICEV (ref.)								
	HEV	−0.072		0.038		0.029		−0.014	
	PHEV	0.045		−0.025		0.042		−0.079	
	BEV	0.207		−0.074		−0.073		0.067	
Vehicle age (years)	0–1 (ref.)								
	2–4	0.000		0.023		−0.053		−0.022	
	5–9	−0.042		0.018		−0.099	*	−0.038	
	10–15	−0.196	**	−0.017		−0.136	**	−0.038	
	>15	−0.271	***	0.007		−0.242	***	−0.028	
Vehicle weight (kg)	<951 (ref.)								
	951–1,150	0.000		0.038		−0.025		0.023	
	1,151–1,350	−0.015		0.022		−0.050		0.044	*
	1,351–1,550	−0.036		0.043		−0.036		0.058	**
	>1,550	−0.065		0.064		−0.041		0.081	***
Gender	Female (ref.)								
	Male	0.124	***	0.026		0.473	***	−0.016	
Age (years)	18–29 (ref.)								
	30–39	−0.015		0.013		0.188	***	0.095	***
	40–49	−0.058		−0.012		0.274	***	0.069	**
	50–59	−0.106	*	0.027		0.231	***	0.048	*
	60–69	−0.222	***	0.075		0.248	***	0.046	.
	70 or above	−0.567	**	−0.083		0.280	***	−0.006	
Education level	Low (ref.)								
	Moderate	0.130	**	−0.029		0.428	***	0.079	***
	High	0.034		0.000		0.529	***	0.056	***
Work status and weekly hours	No jobs (ref.)								
	≤12 (ref.)					−0.042		0.053	
	12–30	0.929	***	−0.030		0.168	***	−0.039	*
	≥30	1.205	***	−0.020		−0.001		−0.091	***
Adults (#)	1 (ref.)								
	2	−0.552	***	0.034		−0.857	***	0.034	.
	≥3	−0.897	***	0.076		−1.409	***	0.036	
Young children (#)	0 (ref.)								
	1	−0.088		−0.012		0.208	***	0.019	
	≥2	−0.294	***	−0.115		0.179	**	0.077	*
Older children (#)	0 (ref.)								
	1	−0.128	**	−0.059		0.119	***	0.121	***
	≥2	−0.275	***	−0.016		0.097	**	0.199	***
Drivers licenses (#)	1 (ref.)								
	2	−0.366	***	0.006		0.146	***	−0.072	***
	≥3	−0.390	***	0.067		0.336	***	−0.155	***
Household income level (quintile)	First (ref.)								
	Second	0.155	*	−0.065		0.051		0.035	.
	Third	0.108	.	−0.097	.	0.050		0.039	.
	Fourth	−0.052		−0.092	.	−0.014		0.055	*
	Fifth	−0.220	***	−0.086		−0.075	*	0.049	*
Urbanization degree	Extreme (ref.)								
	High	0.178	***	0.006		0.120	***	0.029	.
	Moderate	0.201	***	−0.002		0.146	***	0.026	
	Barely or not urbanized	0.216	***	0.052		0.176	***	0.041	*
Supermarkets and grocery stores (#)		−0.004	***	0.000		−0.007	***	−0.002	***
Walkability of train stations		−0.116	*	0.000		−0.005		−0.030	
Cycling accessibility of train stations		−0.123	***	0.004		−0.040	.	−0.016	
Model fit									
AIC (AIC for the null model)		47152.74 (50167.83)				136291.7 (142430.3)			
BIC (BIC for the null model)		47862.59 (50184.78)				137074.2 (142448.6)			

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘’ 1

Table 4
Tobit model results for daily VKT (10 km) by commuting and non-commuting purposes.

		Commuting		Non-commuting	
		Coef.	Sig.	Coef.	Sig.
(Intercept)		−8.539	***	−5.577	***
Year	2018–2019 (ref.)				
	2020	−2.043	***	−1.350	***
Ownership status	Owned (ref.)				
	Leased/company	2.222	***	1.790	***
Powertrain type	ICEV (ref.)				
	HEV	−0.345		0.033	
	PHEV	−0.101		−0.247	
	BEV	0.748		−1.450	*
Vehicle age (years)	0–1 (ref.)				
	2–4	0.292		−0.520	**
	5–9	−0.101		−0.743	***
	10–15	−0.877	**	−1.043	***
	>15	−1.372	***	−1.566	***
Vehicle weight (kg)	<951 (ref.)				
	951–1,150	0.199		0.000	
	1,151–1,350	0.202		0.029	
	1,351–1,550	0.222		0.184	
	>1,550	0.365		0.339	.
Gender	Female (ref.)				
	Male	0.862	***	2.398	***
Age (years)	18–29 (ref.)				
	30–39	−0.220		0.670	***
	40–49	−0.384	.	1.147	***
	50–59	−0.674	**	1.027	***
	60–69	−1.096	***	0.957	***
	70 or above	−1.424	.	1.038	***
Education level	Low (ref.)				
	Moderate	0.649	**	1.857	***
	High	0.689	**	2.621	***
Work status and weekly hours	No jobs (ref.)				
	≤12 (ref.)			0.111	
	12–30	3.791	***	0.712	***
	≥30	5.158	***	0.128	
Adults (#)	1 (ref.)				
	2	−2.365	***	−3.522	***
	≥3	−3.826	***	−5.935	***
Young children (#)	0 (ref.)				
	1	−0.347		0.750	***
	≥2	−1.449	***	0.368	
Older children (#)	0 (ref.)				
	1	−0.575	**	0.348	*
	≥2	−1.291	***	0.040	
Drivers licenses (#)	1 (ref.)				
	2	−1.580	***	0.681	***
	≥3	−1.810	***	1.412	***
Household income level (quintile)	First (ref.)				
	Second	0.454		0.129	
	Third	0.263		0.056	
	Fourth	−0.393		−0.158	
	Fifth	−1.018	***	−0.240	
Urbanization degree	Extreme (ref.)				
	High	0.852	***	0.485	***
	Moderate	0.915	***	0.535	***
	Barely or not urbanized	1.123	***	0.742	***
Supermarkets and grocery stores (#)		−0.014	**	−0.026	***
Walkability of train stations		−0.497	.	0.037	
Cycling accessibility of train stations		−0.425	**	−0.141	
logSigma		2.105	***	2.081	***
Model fit					
AIC (AIC for the null model)		66221.8 (69602.6)		170,785 (177184.4)	
BIC (BIC for the null model)		66585.18 (69619.55)		171185.3 (177202.6)	
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 '' 1.					

4.2. Model results

The hurdle and Tobit models were used to analyze the trip frequency and daily VKT for both commuting and non-commuting travel, as shown in Tables 3 and 4. The highest Variance Inflation Factor (VIF) values for the independent variables were 1.485 and 1.409, respectively, indicating no issues with multicollinearity. After running the models, the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) values were lower than those of the null models, indicating a good fit for each model.

4.2.1. Hurdle model results

The hurdle model results (Table 3) suggest that, for commuting purposes, leased or company cars were associated with a higher probability of trips compared to privately owned cars. However, no correlation was found between powertrain types and the probability or frequency of trips. Individuals with a moderate education level were more likely to commute by car than those with lower education levels. Additionally, individuals in paid employment who work more hours had a higher probability of commuting by car compared to those commuting for study or voluntary work. Household composition also influenced commuting behavior: more adults in the household and the presence of younger or older children reduced the likelihood of commuting by car. A higher number of licensed drivers in the household was negatively associated with the probability of commuting by car. In terms of income, those in low-middle income households were more likely to commute by car than those in low-income households, whereas individuals in the highest income bracket had a lower probability of commuting by car. Living in less urbanized areas, having limited access to convenience facilities, and poor access to walkable or cycling-accessible train stations were all associated with a higher likelihood of commuting by car. Finally, people were less likely to commute by car in 2020 than in 2018–2019, likely due to COVID-19 travel restrictions.

For non-commuting trips, leased or company cars had a higher probability of being used compared to privately owned cars. However, powertrain type did not significantly influence the likelihood or frequency of making non-commuting trips. The probability of using older cars (5 years and over) for non-commuting trips was significantly lower compared to newer cars, while heavier cars were associated with a higher frequency of such trips. Gender and age also played a role: males were more likely than females to make non-commuting trips by car, and older individuals were more likely than younger individuals to do so. Middle-aged individuals (30–59 years old) showed a higher frequency of non-commuting trips. Higher levels of education were associated with both an increased probability and frequency of non-commuting car trips. People working moderate hours (12–30 h per week) were more likely to make non-commuting trips, while those with longer working hours showed a reduced frequency. A greater number of adults in the household was linked to a lower likelihood of non-commuting trips while having younger or older children increased both the probability and frequency of these trips. A higher number of licensed drivers in the household was correlated with a higher probability but a lower frequency of non-commuting trips. Individuals in the highest income households had a lower probability of making non-commuting trips, but those in higher income brackets generally showed an increased frequency of these trips. Negative urbanization effects—such as living in less urbanized areas, limited access to conveniences, and fewer cycling-accessible train stations—were linked to both a higher probability and frequency of non-commuting trips. Finally, the likelihood of making non-commuting trips by car was lower in 2020 compared to 2018–2019, likely reflecting the impact of COVID-19 on travel behavior.

4.2.2. Tobit model results

The Tobit model results (Table 4) indicate that for commuting trips, leased or company cars were associated with longer daily VKT compared to privately owned cars. However, no significant correlation was found between powertrain types and daily VKT for commuting purposes. Vehicles aged 10 years and older were linked to shorter daily VKT compared to newer cars. Males tended to drive longer daily VKT for commuting than females, while individuals aged 50–59 years drove shorter daily VKT than younger adults. Higher education levels correlated with longer daily VKT for commutes, and employed individuals with longer working hours were also more likely to have increased daily VKT. Households with fewer adults and children (both younger and older) tended to have longer daily VKT, whereas those with more licensed drivers had shorter daily VKT for commuting. Compared to low-income households, those in the highest income bracket generally drove longer daily VKT for commuting. Additionally, living in less urbanized areas, having limited access to convenience facilities, and poor cycling accessibility to train stations were associated with longer daily VKT for commuting. Finally, individuals were less likely to drive longer daily VKT for commuting in 2020 compared to 2018–2019, likely due to the impact of COVID-19.

For non-commuting trips, leased or company cars were driven for longer daily VKT compared to privately owned cars. Among powertrain types, only BEVs were significantly associated with shorter daily VKT for non-commuting purposes compared to ICEVs. Older cars were linked to shorter daily VKT than newer models. Males tended to have longer daily VKT for non-commuting trips than females, while older individuals also tended to drive longer daily VKT compared to younger adults. Higher education levels were linked to longer daily VKT for non-commuting travel. Individuals with moderate working hours had longer daily VKT for non-commuting compared to those without jobs. Households with more adults were associated with shorter daily VKT for non-commuting purposes, and the presence of younger and older children correlated with shorter daily VKT. Conversely, households with more licensed adults were linked to longer daily VKT for non-commuting trips. Living in less urbanized areas and having limited access to conveniences were correlated with longer daily VKT for non-commuting trips. Finally, daily VKT for non-commuting reasons was shorter in 2020 compared to 2018–2019, likely reflecting the impact of COVID-19 on travel behavior.

5. Discussion

5.1. Main findings

5.1.1. Effect of vehicle attributes on vehicle usage

This section discusses how vehicle attributes, particularly ownership status and powertrain type, are correlated with vehicle usage patterns. Our model results indicate that leased or company cars are associated with a higher likelihood of making trips and longer daily VKT for both commuting and non-commuting purposes compared to privately owned cars. This suggests that ownership status and the related cost structures play a significant role in vehicle usage, irrespective of powertrain type. In our study, PHEVs and BEVs that are not privately owned were predominantly company vehicles. Employers often cover all or part of the operating costs, including both business and private kilometers, which makes the per-kilometer cost of using a company vehicle substantially lower than that of a privately owned vehicle. Additionally, both company and privately leased vehicles typically come with maintenance packages, reducing concerns about repair costs and encouraging more extensive driving compared to privately owned vehicles, where maintenance costs are the owner's responsibility. Moreover, drivers of leased or company vehicles generally feel less concern about depreciation and resale value, which can lead to increased driving frequency. In contrast, private car owners may limit their driving to preserve their vehicle's resale value. These cost advantages likely contribute to the higher probability of making trips and longer VKT for leased and company vehicles compared to privately owned ones. This finding aligns with trends in the Netherlands, where privately owned cars averaged 31.69 km per day in 2019 and 26.30 km in 2020, significantly lower than company cars, which averaged 60.13 km and 46.30 km in those same years (CBS, 2021).

In examining the impact of powertrain type on vehicle usage, our model results show that after controlling for various factors—particularly ownership status—BEV powertrains are significantly associated with shorter daily VKT for non-commuting purposes compared to other powertrain types. This finding aligns with previous studies that found lower BEV usage in Ireland (Weldon et al., 2016) and Germany (Habla et al., 2021), as well as lower PEV usage in the US (Burlig et al., 2021; Davis, 2019) compared to ICEVs. One possible explanation for this is range anxiety, which may cause BEV users to limit their trips to avoid running out of battery. As a result, BEVs are often used for shorter non-commuting trips. In contrast, PHEVs do not exhibit the same pattern of shorter daily VKT, suggesting that range anxiety is less of a concern for PHEV users. The internal combustion engine in PHEVs provides a backup for electric driving, enabling them to be used for both commuting and non-commuting purposes without the same constraints on trip length seen with BEVs. Another possible explanation is self-selection: individuals who typically drive shorter distances may find BEVs more suitable for their needs, leading them to adopt and use these vehicles. Our sample data supports this, as the largest share of BEV users resides in highly urbanized areas, where non-commuting trips are generally shorter. Additionally, BEV users may differ from ICEV users in ways that influence their travel behavior, such as having stronger environmental motivations, which could naturally limit their vehicle usage. This points to a potential self-selection effect as well.

When comparing BEV usage for commuting versus non-commuting purposes, our model results reveal that BEVs are driven significantly fewer kilometers per day for non-commuting trips compared to ICEVs. However, this effect does not occur for commuting trips. One possible explanation for this difference is that non-commuting trips are often incidental and may be longer, while commuting trips are typically regular and predictable, providing more certainty regarding the required driving range and availability of charging options. As a result, BEV users may feel more constrained by range limitations for non-commuting trips, leading them to avoid longer journeys. Another explanation is that BEVs might be prioritized for commuting over non-commuting use. In the Netherlands, many BEVs are company cars, which are typically designated for commuting. After completing their commute, employees may find that reduced battery charge, coupled with potential driver fatigue, discourages additional non-commuting trips.

When further analyzing the impact of powertrain type on vehicle usage, our model results also reveal that the use of BEVs and PHEVs does not lead to increased usage—measured by daily trip frequency and VKT—for both commuting and non-commuting purposes compared to ICEVs. This finding suggests there is no significant evidence that BEV and PHEV powertrains in single-car households in the Netherlands result in a rebound effect, in contrast to ICEVs and HEVs. Our results differ from previous studies that found increased PEV usage in Greater Stockholm (Langbroek et al., 2017) and higher BEV usage in Norway (Simsekoglu, 2018), both attributed to lower operating costs. However, our findings are consistent with those of Chakraborty et al. (2022), who found no correlation between operating costs and PEV usage in the US.

Older cars are less likely to be driven and have shorter daily VKT for both commuting and non-commuting purposes compared to newer vehicles. Heavier, often larger cars are associated with more frequent non-commuting trips. This aligns with findings from Ou et al. (2020) and Huo et al. (2012), who observed that larger and newer vehicles generally accumulate higher annual VKT. Newer and larger cars may encourage more driving due to their higher cost, prompting owners to use them extensively to justify the expense. Additionally, these vehicles often serve as status symbols, reflecting wealth and personal taste (Ou et al., 2020). There may also be a self-selection effect, where individuals with higher driving needs are more likely to opt for heavier and larger cars.

Overall, our model results indicate no significant correlation between powertrain type (ICEV, HEV, PHEV, or BEV) and daily VKT for commuting purposes. However, BEVs are significantly associated with shorter daily VKT for non-commuting trips compared to ICEVs. This suggests that the higher daily VKTs observed among BEV and PHEV users for both commuting and non-commuting purposes, relative to ICEV and HEV users in the descriptive statistics, are likely driven by variations in the personal and spatial characteristics of car users, along with other vehicle attributes, rather than the powertrain itself. Importantly, this difference can largely be attributed to the fact that BEVs and PHEVs are predominantly leased or company cars, highlighting the importance of ownership status over powertrain type.

5.1.2. Effect of socioeconomic and demographic characteristics on vehicle usage

Compared to females, males have a higher probability of driving for both commuting and non-commuting reasons, and they also tend to have longer daily VKT for these trips. These findings align with previous research on ICEV usage (Akar & Guldmann, 2012; Havet et al., 2021; Julsrud, 2014) and PEV usage (Farkas et al., 2018; IEA, 2018). However, these results contrast with those of Boarnet and Crane (2001) in the U.S., which found that women tend to make more non-commuting trips by car than men.

Individuals aged 50 and older are less inclined to use cars for commuting and tend to have shorter daily VKT for commuting purposes compared to younger adults aged 18–29. However, for non-commuting trips, older adults are more likely to use their cars and generally have longer daily VKT. Additionally, the frequency of non-commuting car trips increases among middle-aged individuals (30–59 years old). Our findings are somewhat consistent with Akar and Guldmann (2012), who found that younger ICEV users have higher VKT than older users. They also partly align with Julsrud (2014)'s observation that ICEV users aged 35–44 make more trips per day than those in other age groups.

A higher level of education is associated with an increased likelihood and frequency of making non-commuting trips by car, as well as longer daily VKT for both commuting and non-commuting purposes. Individuals with moderate education levels also contribute to the likelihood of making commuting trips by car. This finding aligns with Akar and Guldmann (2012), who reported that drivers of ICEVs with higher education levels tend to have greater annual VKT than other groups, regardless of travel purpose. Similarly, Langbroek et al. (2017) found that compared to ICEV users, PEV users—who are typically more highly educated and wealthier—make significantly more trips and account for a larger percentage of their total daily travel distance in car use.

Having more adults in the household is negatively correlated with the probability of making car trips and with longer daily VKT for both commuting and non-commuting purposes compared to single-adult households. However, the number of adults in the household is not associated with the frequency of making car trips for either commuting or non-commuting purposes. This finding partially aligns with Dieleman et al. (2002), who noted that in the Netherlands, an increase in households with two working adults does not necessarily lead to increased ICEV usage.

Compared to child-free households, those with children of any age are less likely to make car trips for commuting and thus have shorter daily VKT. However, these households are more likely to make non-commuting trips and so have longer daily VKT for these.

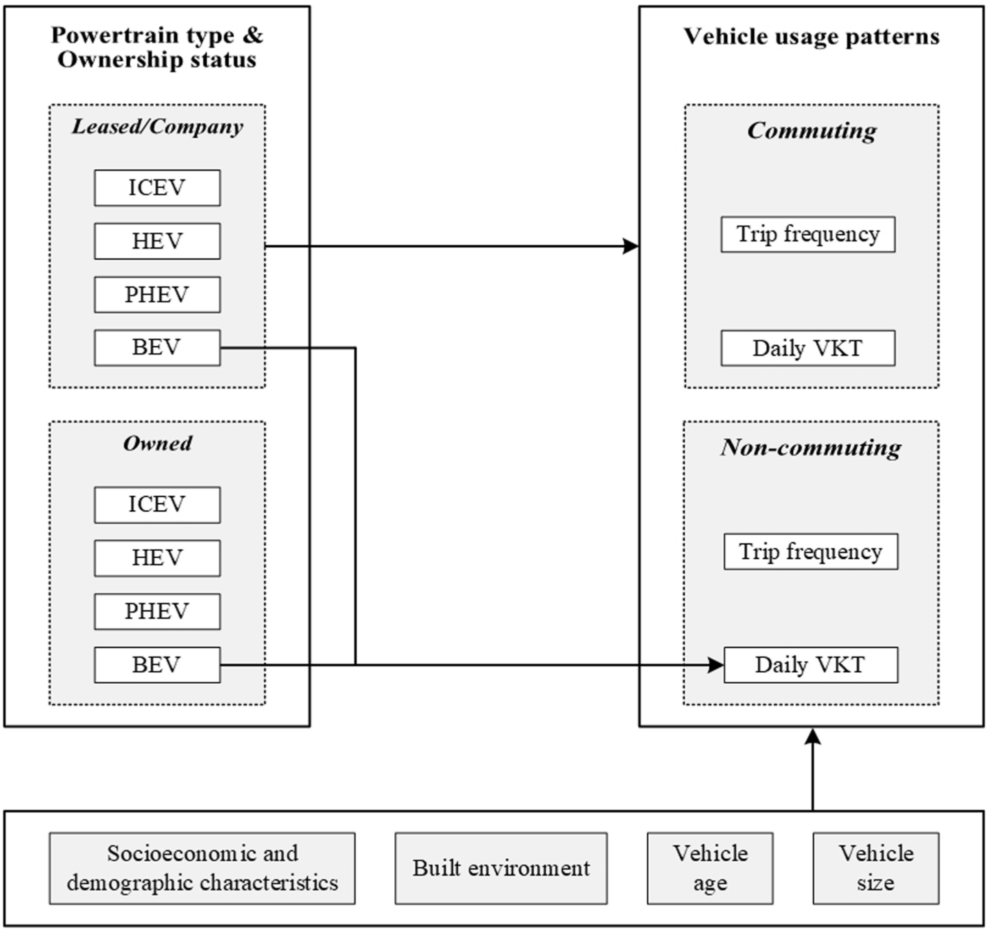

Fig. 2. Summary of research findings with arrows indicating the direction of significant correlations.

This finding partially aligns with previous studies (Akar & Guldmann, 2012; Boarnet & Crane, 2001; Dieleman et al., 2002; Ye et al., 2018), which suggest that parents use their cars to transport children to school, sports events and other recreational and educational activities.

Households with more licensed drivers are less likely to make commuting trips by car and tend to have lower daily VKT for commuting. They also experience fewer non-commuting trips by car. Conversely, having more licensed drivers increases the likelihood of non-commuting trips by car and results in higher daily VKT for those trips. This may occur in single-car households, where competition for the car use arises for commuting. With more drivers available, the car is often used for leisure activities, allowing individuals to take turns driving. This finding aligns with Chakraborty et al. (2022), who noted that an increase in the number of drivers leads to a higher share of PEV VKT within total household VKT in multi-car households, without distinguishing between travel objectives.

Households in the lower-middle income bracket are positively correlated with the probability of commuting trips by car. In contrast, the highest-income households tend to have a lower probability of commuting by car and exhibit shorter daily VKT for commuting. For non-commuting trips, the highest-income households show a reduced likelihood of making car trips, while higher-income households generally increase the frequency of non-commuting trips. These findings partly align with Boarnet and Crane (2001), who found that non-commuting car trips increase among middle-income households and decrease among high-income households in the U.S. Similarly, Dieleman et al. (2002) found that higher-income individuals in the Netherlands are more likely to own and use a private car. Abdullah et al. (2021) noted that higher-income groups in the U.S. have greater household VKT, while Akar and Guldmann (2012) identified a positive correlation between monthly household income and the number of non-commuting trips in Pakistan.

5.1.3. Effect of the built environment on vehicle usage

Reduced levels of urbanization—characterized by lower address density, fewer supermarkets and grocery stores, and diminished walkability and cycling accessibility to train stations—are significantly associated with a higher probability of taking car trips and longer daily VKT for both commuting and non-commuting travel. Additionally, less urbanized areas are correlated with an increased frequency of non-commuting car trips. These findings align with previous studies (Akar & Guldmann, 2012; Chakraborty et al., 2022; Figueroa et al., 2014; Nickkar et al., 2020), which have shown that individuals living in less urbanized areas with limited access to public services, including transportation, tend to have higher VKT.

5.1.4. Effect of COVID-19 on vehicle usage

The model results indicate that in 2020, individuals experienced a reduced probability and frequency of driving, along with shorter daily VKT for commuting purposes, compared to 2018 + 2019. A similar trend was observed for non-commuting trips, where there was a decline in both the likelihood of driving and daily VKT in 2020. This decrease in car travel behavior is likely attributable to the widespread impact of the COVID-19 pandemic, which introduced lockdowns, remote working, and social distancing measures. These restrictions significantly altered daily routines and mobility patterns. With more people working from home and fewer social and recreational activities, daily commuting diminished, and the overall frequency of car use decreased. Additionally, concerns about health and safety may have further discouraged non-essential travel, contributing to the observed decline in daily VKT. A summary of our key research findings is presented in Fig. 2.

5.2. Policy implications

The findings of this study suggest that in single-car households in the Netherlands, BEV and PHEV powertrains do not lead to a rebound effect, allowing for more sustainable car travel without increasing congestion. Our findings suggest that PHEVs could effectively replace ICEVs and HEVs in single-car households in the Netherlands. However, BEV users may face challenges on longer non-commuting trips, potentially due to range limitation. To address this, we recommend expanding charging infrastructure and increasing fast-charging availability, making charging more convenient and alleviating range anxiety for BEVs.

Our findings indicate that leased or company vehicles, particularly BEVs and PHEVs, are used more frequently and travel greater distances per day than privately owned vehicles. This underscores the need for policies that reduce incentives encouraging leasers and employees to maximize the use of these vehicles. Instead, the focus should shift towards encouraging more environmentally friendly alternatives. Employers can play a crucial role by offering mobility packages that promote sustainable transport options, such as public transport, walking, cycling, and shared micro-mobility. Additionally, shared BEVs and PHEVs could offer a promising solution for more sustainable vehicle use. With shared modes, users pay based on the kilometers driven, reducing the incentive to drive more simply to justify fixed costs associated with ownership or leasing. It aligns with a planned Dutch policy, set to take effect by 2030, which will tax vehicle owners based on actual kilometers driven rather than a fixed ownership fee plus usage costs (Government of the Netherlands Rijksoverheid, 2022).

Moreover, our research sheds light on potential transport externalities related to BEV and PHEV usage, particularly concerning ownership models. Contrary to assumptions that lower operating costs of electric powertrains would increase driving, we found that leased or company vehicles—regardless of powertrain type—are used more intensively, with higher daily VKT and higher probability of trip making for both commuting and non-commuting purposes. Given the large share of BEVs and PHEVs in leased or company fleets in the Netherlands, our findings highlight the critical role of ownership models in shaping transport externalities. While BEVs and PHEVs reduce tailpipe emissions and help lower air pollutants compared to ICEVs, their intensive use could contribute to additional externalities. These externalities include particulate matter (PM) emissions from brake and tire wear, increased road wear, congestion, and higher parking demand in urban areas (Cavallaro & Nocera, 2023; Ward et al., 2021; Woo et al., 2022). In addition, higher VKT due to lower operating costs could contribute to urban sprawl, potentially undermining sustainable development goals (Haghani et al., 2024). This suggests that policies aiming to reduce transport externalities should focus not only on encouraging the shift to EVs but also on addressing ownership models. For instance, policymakers can leverage these insights to design targeted interventions, such as usage fees on leased and company BEVs and PHEVs, to mitigate the negative effects of high vehicle use (Cavallaro et al., 2024).

6. Conclusion

This paper examined the usage patterns of ICEVs, HEVs, PHEVs, and BEVs in single-car households, analyzing daily trip frequency and VKT for both commuting and non-commuting travel, and identified factors associated with vehicle usage patterns. We compared the usage of EVs, particularly BEVs and PHEVs, with ICEVs to assess whether EVs can effectively replace ICEVs on a daily basis. The descriptive analysis revealed significant differences in daily VKT for both commuting and non-commuting trips among the four vehicle user groups. Notably, BEV and PHEV users generally exhibit longer daily VKT for both commuting and non-commuting travel compared to ICEV and HEV users.

Our model results suggest that vehicle attributes, along with socioeconomic, demographic, and built environment factors, correlate with daily car trip frequency and VKT, varying by travel purpose. First, ownership status significantly influences car usage: drivers of leased or company vehicles have a higher probability of making car trips and covering longer daily VKT for both commuting and non-commuting travel compared to those with privately owned vehicles. Second, BEVs display distinct usage patterns, with significantly shorter daily VKT for non-commuting trips compared to other powertrain types with the same ownership status, a pattern not observed for commuting trips. The distinction may relate to range anxiety or the self-selection of BEV users managing range concerns. Third, our findings do not support a rebound effect with BEV and PHEV powertrains in single-car households in the Netherlands. Finally, while descriptive analysis suggests that BEV and PHEV users have longer daily VKT than ICEV and HEV users for both commuting and non-commuting trips, our model results reveal that these differences are primarily driven by other factors such as ownership status rather than the powertrain type itself.

Future research could address several important issues related to the usage of EVs. While our analysis focused on single-car households, the largest group of car-owning households in the Netherlands, PHEVs and BEVs are more commonly adopted by multi-car households. Future studies could explore whether a rebound effect occurs with PHEV and BEV use in these households. Additionally, our findings are specific to the Dutch context and based on data from 2018 to 2020, which should be considered. Variations in EV and ICEV usage may arise in different geographic and temporal contexts due to factors such as location, availability of charging infrastructure, cost per kilometer (e.g., electricity versus gasoline prices), tax regulations, subsidies, and leasing conditions. Notably, local and national policies will play a large role in shaping the conditions for EV ownership and use, leading also to differences in trip frequency and VKT by purpose. Comparative studies across various regions and using more recent data could provide further insights. Ongoing research should also examine the evolving role of range anxiety among BEV users, especially with advances in battery technology and faster charging options.

While our study finds no significant evidence of a rebound effect—where BEV and PHEV powertrains lead to higher car usage compared to ICEVs—this conclusion is based on the limitations of our study design. The cross-sectional nature of the data restricts our ability to capture long-term behavioral changes associated with car ownership, particularly in distinguishing whether observed usage patterns result from lower costs or are influenced by factors like range anxiety and self-selection. Future research utilizing longitudinal data or experimental designs would be better suited to identify causal relationships between powertrain types and travel behavior, providing a more definitive assessment of the rebound effect in the context of electrified transportation.

Finally, our study focused on the private usage of PHEVs and BEVs in the transition from ICEVs. While this transition is crucial for reducing GHG emissions in the transportation sector, it is not a panacea as it does not fully address other challenges like traffic safety and urban congestion. Additionally, the production and operation of EVs require raw materials and significant energy, leading to environmental and social impacts on local communities (Cano et al., 2018). Despite these complexities, the shift from private ICEVs to EVs is essential for sustainable transportation practices and remains a key environmental policy goal in many regions (De Vos, 2024). Understanding this shift is fundamental for evaluating broader impacts, such as emission reductions and traffic congestion. Future research could explore these effects related to BEV and PHEV usage. Furthermore, creating a more sustainable transportation system requires reducing car dependency and promoting alternative modes of transportation, including shared EVs, micromobility options, and especially cycling and walking.

CRediT authorship contribution statement

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

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.

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