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Exploring the macro environment determinants behind the diffusion of electric Light Commercial Vehicles

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Abstract

Rising transport emissions undermine urban sustainability goals, exposing a widening gap between climate ambition and emissions trajectories. Amid these trends, in the European Union (EU), electric vehicles account for only a very small proportion of new registrations for Light Commercial Vehicles (LCVs), below the levels seen in the passenger vehicles segment. While previous studies have investigated country-specific factors, this research adopts a macro-level perspective by examining aggregate diffusion patterns of electric Light Commercial Vehicles (eLCVs) across 27 EU member states. To identify the underlying determinants of this variation, this study employed a series of panel data regression models to evaluate how a set of socioeconomic, energy, mobility, and innovation-related variables shape eLCV diffusion and, more specifically, to assess the explanatory power of these variables. Among the models tested, the Fixed Effects Model proves to be most effective in capturing these relationships, reinforcing the value of a multifactorial approach to understanding eLCV adoption dynamics. The findings enhance the understanding of structural diffusion patterns and provide an empirical basis for better aligning policy and industry efforts with the EU's regional decarbonisation objectives.

Keywords Electric vehicles · Light commercial vehicles · Innovation diffusion · Panel data regression model · Electrification policies

Abbreviations

EAFO	European Alternative Fuels Observatory
eLCV	Electric Light Commercial Vehicle
EU	European Union
EV	Electric Vehicles
FEM	Fixed Effects Model

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GDP	Gross Domestic Product
GHG	Greenhouse Gas
HEV	Hybrid Electric Vehicles
LCV	Light Commercial Vehicles
LSDV	Least Squares Dummy Variable
OLS	Ordinary Least Squares Model
PPP	Power Purchase Parities
R&D	Research and Development
REM	Random Effects Model

Introduction

In recent years, the decarbonisation of the transportation system has gained significant attention from governments, researchers, the private sector, and citizens. Road transport accounted for more than 22% of total European Union (EU) greenhouse gas (GHG) emissions in 2021 (UNFCCC 2024). Multiple actors advocate for introducing policy measures and behavioural changes to reduce the transport sector's GHG emissions. Underpinning these efforts, the European Green Deal sets ambitious targets, aiming for a minimum 55% reduction in transport emissions by 2030 compared to 1990, with the ultimate goal of achieving net-zero GHG emissions by 2050 (European Commission 2024). The key objective is to improve the uptake of clean vehicles and alternative fuels considerably (European Commission 2024).

Despite implementing various policy measures, Light Commercial Vehicles¹ (LCV) remain a significant source of GHG emissions. The emission rates for LCV surpass those of other road transport modes, while the diffusion rates of electric vehicles² (EVs) remain relatively low (UNFCCC 2024). As illustrated in Fig. 1, electric Light Commercial Vehicles (eLCV) comprise only 0.75% of the total LCV stocks in the EU as of 2022 (European Alternative Fuels Observatory 2024). In contrast, the registration rate for electric passenger cars was 1.2%. However, the diffusion of EVs is on the rise, with a 37% increase in eLCVs registrations between 2021 and 2022. The number of eLCVs registered rose from 44,717 in 2021 to 61,401 in 2022 (European Alternative Fuels Observatory 2024).

Within the EU, the diffusion of eLCVs varies across countries. Figure 2 highlights this disparity, with countries such as Germany and Sweden achieving higher eLCV diffusion rates of 14.4% and 14.6% between 2013 and 2022. Bulgaria, Cyprus, Estonia, Greece, Poland and Romania show limited EVs integration in the total number of LCVs stock, around a 0.1% share, and diffusion rates remaining below 0.5% over the same period, reflecting a slower and more gradual uptake.

¹Light commercial vehicles (LCVs) are classified as N1 vehicles within the European Union's vehicle classification system, in line with United Nations Economic Commission for Europe standards (European Commission 2025) and defined by Regulation (EU) 2018/858 of the European Parliament and Council (European Commission 2018), which establishes a framework for the approval of motor vehicles and their trailers. According to the classification, N1 vehicles are those used for the carriage of goods with a maximum mass not exceeding 3.5 tonnes.

²Electric vehicles (EVs) refer to Battery Electric Vehicles, also known as all-electric or 100% electric vehicles. These vehicles exclusively operate on an electric motor, without any secondary source of propulsion (European Alternative Fuels Observatory 2025).

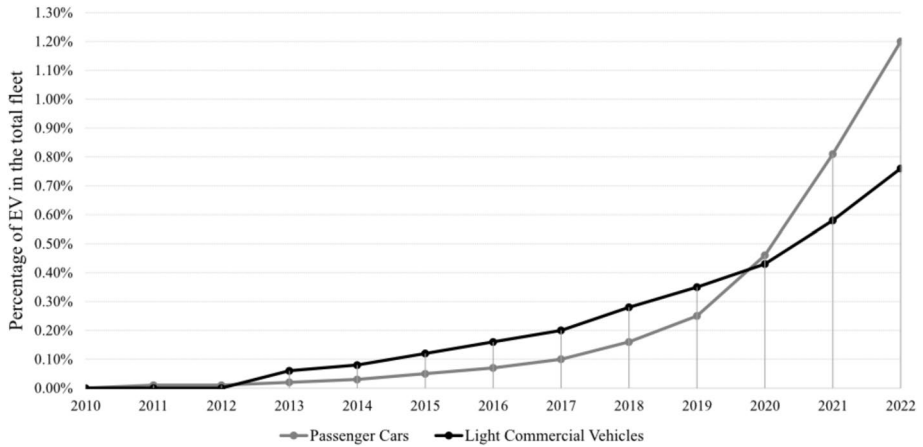


Fig. 1 Diffusion of EVs in the EU (Author’s analysis, European Alternative Fuels Observatory 2024)

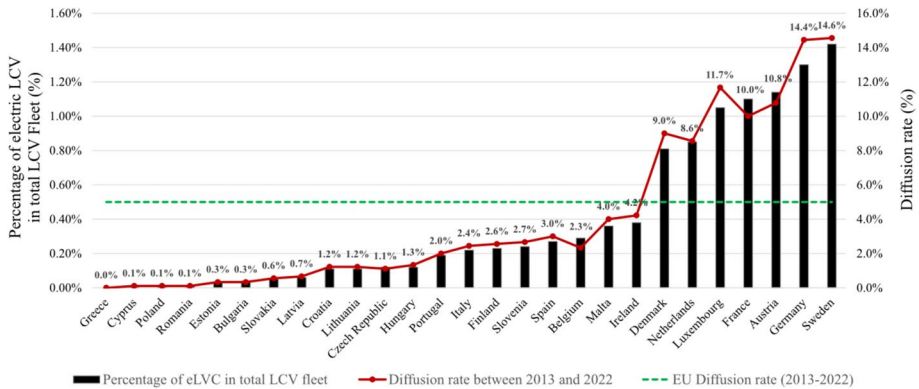


Fig. 2 EU countries’ share of eLCVs and respective diffusion rate in 2022 (Author’s analysis, European Alternative Fuels Observatory 2024). *Note:* The diffusion rate represents the annual growth rate of eLCVs registrations from 2013 to 2022

Figure 2 highlights the disparities between countries, indicating that multiple determinants may influence diffusion. While the diffusion of eLCVs varies across EU member states, as shown in Fig. 2, this study does not perform a country-by-country comparative analysis. Instead, we analyse aggregate diffusion patterns across all 27 EU countries to identify common macro-level drivers influencing adoption. Indeed, according to diffusion theory, eLCV diffusion occurs at different paces and stages and is influenced by diverse diffusion environments (Ribeiro and Cherobim 2017; Rogers 1962). Therefore, this research aims to characterise the innovation environment influencing the diffusion of eLCVs by identifying the key variables shaping this process. Given that LCVs are predominantly owned by organisations and businesses, serving various purposes, including urban freight services, such as parcel and delivery services, utilities, mobile services, and construction applications, understanding their adoption patterns is especially relevant.

While previous studies often focus on country-specific case studies, this study investigates macro-level variables affecting eLCV diffusion across all 27 EU countries. To this end, the research asks: *What macro-level variables are associated with the diffusion of eLCVs across the European Union?* Accordingly, the main objectives are (i) to assess and characterise the innovation environment and (ii) to identify variables influencing eLCVs' diffusion across the EU at an aggregate level.

This study's main contribution lies in its comprehensive and exploratory investigation of the variables behind the diffusion of eLCVs, offering insights for diffusion models, policies, and business strategies for logistics firms and energy and infrastructure providers. By modelling the relationship between the diffusion of eLCVs and the diffusion environment, this study highlights the need to better understand the nuanced interplay between financial incentives, energy policies, and the critical role of charging infrastructure in the diffusion of eLCVs.

Methodologically, the study employs hypothesis-driven panel data regression analysis to focus on overarching diffusion patterns over time by modelling relationships between key explanatory variables. The hypotheses are based on a literature review of diffusion determinants, including studies on LCVs, passenger vehicles, and other green technologies (see Appendix B, Tables B2 and B3), and are further detailed in Section “[Literature review](#)”.

The remainder of this article is structured as follows: Section “[Literature review](#)” includes a literature review that covers research on the diffusion of eLCVs and identifies the main factors impacting the diffusion of EVs. Section “[Methods and materials](#)” provides insights into the methods and materials, including the formulation of hypotheses and a description of the methods employed to test these hypotheses. Section “[Results](#)” presents the key results, while Section “[Discussion](#)” discusses the main findings. Finally, Section “[Conclusions](#)” concludes by emphasising policy implications and offering recommendations for further research.

Literature review

The innovation diffusion theory was first introduced by Rogers (1962), marking the starting point for most research on the diffusion of innovation. According to Rogers (1962), diffusion is the process of communicating new ideas and innovations over time through specific channels within a social system. This process inherently involves both spatial and temporal dimensions. Spatially, diffusion can vary across regions, countries, markets, or socioeconomic systems. At the same time, temporally, it unfolds over a period, often years, with varying speeds (referred to as “rates of adoption”). In this study, the term “diffusion dynamics” refers to variations in the speed and manner of adoption. The diffusion, or diffusion process, is shaped by the “diffusion environment,” which encompasses both internal and external conditions that influence the spread of an innovation or technology (Ribeiro and Cherobim 2017). Ribeiro and Cherobim (2017) explored the importance of innovation environment indicators by analysing the literature and systematising the results of empirical research. Their study established the critical role of the innovation environment in shaping organisational strategies and its impact on technology adoption, emphasising that comprehending the characteristics is vital for understanding technology diffusion (Ribeiro and Cherobim 2017).

The diffusion of eLCVs involves several key actors: primarily businesses and organisations that use LCVs in their operations and are the adopters of innovation. Policymakers and governments play a key role in fostering eLCV adoption by developing regulations, incentives, and infrastructure. Additionally, the customers of LCV owners are the end-users of logistic services, such as individuals purchasing parcels or requesting specific delivery services. Their preferences and demand for sustainable logistics solutions influence the market, indirectly affecting the adoption of eLCVs.

According to Ribeiro and Cherobim (2017), there are two distinct categories of innovation environment, considering the proximity between the organisation and environmental variables: the micro-environment and the macro-environment. Micro-environment variables directly impact the organisation (in our case, the eLCVs adopters), encompassing factors within the organisation and its relationships and interactions with external stakeholders such as customers, suppliers, and competitors. The macro-environment comprises variables that can directly and indirectly affect the adopter, but these variables are not directly linked to the organisation's internal operations. These include broader political, social, economic, cultural, and technological factors that collectively influence the overall context in which innovations are developed and adopted. Macro-environment variables are the primary focus of this research.

The diffusion of electric Light Commercial Vehicles

A structured protocol was developed to guide the literature review process, following three steps: design, selection, and analysis (Table A1). In the selection phase, targeted literature searches were conducted using specific search strings across the Web of Science and Scopus databases, yielding 470 studies. The analysis phase included screening titles and abstracts against predefined criteria using Rayyan software to manage references and exclusions. After in-depth reviews, a final set of articles was selected, further filtering aligned with the study objectives, as detailed in Table A2.

This literature review identified three distinct categories of studies: (1) studies examining the decision-making process for adopting EVs, exploring factors and barriers and consumer behaviour and perspectives; (2) studies employing techno-economic and environmental assessments of eLCVs, evaluating their performance, lifecycle costs, and environmental impacts; (3) and studies analysing eLCVs diffusion dynamics, focusing on market penetration and identifying key determinants of diffusion (see Appendix B).

Most studies focused on consumer behaviour and perspectives, often relying on extensive surveys and interviews. While these studies identified several barriers to eLCVs' adoption, such as high upfront vehicle costs and limitations related to battery technology or charging infrastructures (Anosike et al. 2021; Saxena and Yadav 2023; Sonar et al. 2023), they generally lack empirical analysis of broader adoption trends (Galati et al. 2021; Melander and Nyquist-Magnusson 2022; Qasim and Csiszár, 2021). Other commonly cited challenges include operational complexities, such as grid constraints, routing issues, limited charging network availability (Mohammed et al. 2020), and concerns over technological immaturity, particularly regarding battery lifetime, charging time, or driving range (Galati et al. 2021; Melander and Nyquist-Magnusson 2022).

For example, Qasim and Csiszár (2021) surveyed transport logistics professionals in Budapest and identified barriers hindering EV adoption, focusing on logistic and vehicle

characteristic constraints. These include limited vehicle range, lengthy recharging times, and inadequate placement of charging stations, all of which are critical factors for improving the vehicle's practicality and alleviating user range anxiety. Similarly, Galati et al. (2021) demonstrated the feasibility of eLCVs for the short food supply chain in Italy, adopting a multi-stakeholder approach based on interviews. Their findings suggest that eLCVs are viable for this sector as they align with its requirements for short-distance trips and moderate cargo weights.

Despite growing academic interest, few studies have examined the innovation diffusion process of eLCVs in depth. In particular, there remains a lack of empirical analysis of the diffusion environment and its key determinants. Notably, a small number of studies employ system dynamics approaches to explore the broader adoption trends of EV technologies. For instance, Pasaoglu et al. (2016) presented a system dynamics simulation model exploring the powertrain technology transition in the EU's light-duty vehicle road transport sector until 2050. Assessing five scenarios, the study examined variables such as oil prices, Gross Domestic Product (GDP) growth, subsidies, and emissions targets. While based on simplifications and assumptions, the model provided valuable insights for strategic policymaking and investment planning within the road transport sector, highlighting the significant role of emission standards and subsidies in reducing CO₂ emissions, lowering energy consumption, and improving the electric vehicle market share (Pasaoglu et al. 2016). Similarly, Cagliano et al. (2017) applied a system dynamics model rooted in Bass Diffusion Theory to explore the adoption of low-impact commercial vans in Turin, Italy. This study identified factors such as advertising, green branding, and word-of-mouth as important drivers while acknowledging that the model did not fully capture operational costs and infrastructure availability. Together, these modelling efforts underscore gaps in the current literature regarding the complexities of the diffusion, particularly the limited integration of systemic variables and the lack of empirical analysis linking institutional, technological, and infrastructural conditions to the diffusion of eLCV.

The literature review reveals that most research focuses on factors influencing eLCVs' adoption from the perspectives of vehicle buyers and companies, primarily examining the decision-making processes. While important, this approach lacks a comprehensive analysis of the external and contextual elements that shape national-level diffusion patterns. A significant gap remains in the empirical literature on diffusion processes, particularly in the systematic identification of key determinants shaping the diffusion environment of eLCVs.

Understanding the diffusion process of eLCVs is crucial for explaining the disparities in eLCV uptake between countries, as highlighted in Fig. 2. To bridge this gap, it is relevant to transition beyond characterising buyer and company perspectives and adopt a more holistic approach to explaining the dynamics driving the diffusion of eLCVs. The second part of the literature review (included in the following section) adopts a broader approach to identifying the key determinants shaping the diffusion process. It specifically examines and analyses the critical factors influencing eLCVs adoption across socioeconomic, governance, technological, and environmental domains, laying the foundation for further investigation.

Determinants of eLCVs diffusion

In this second part of the literature review, the protocol was modified to identify the determinants of technology diffusion, focusing on EVs and, more specifically, eLCVs. The protocol

included problem formulation, eligibility criteria, and search strategies, as detailed in Table B1 in Appendix B. Following in-depth reviews, a curated selection of 38 studies was finalised and is presented in Table B2. For each study, the variables analysed were systematically organised (see Appendix B, Table B3), and the relationships and conclusions regarding each variable's influence on the diffusion of the specific innovation were identified. The systematisation process has identified four key variable typologies, which are detailed and described in the following sections and systematised in Fig. 3: Socioeconomic; Policies and Governance; Environmental and energy; Transport and technology.

Socioeconomic variables

In the literature, GDP per capita consistently emerges as a significant factor in EV diffusion. Per capita GDP is often associated with greater affordability of EVs, as higher national incomes typically enable both increased individual purchasing power and higher government resources to invest in EV infrastructure and incentives. Numerous studies have highlighted a correlation between economic prosperity and the adoption of sustainable



Fig. 3 Macro-environment variables identified per typology

transportation (Agan and Balcilar 2022; İmre et al. 2021; Qin et al. 2022; Zimm 2021). For instance, Agan and Balcilar (2022) suggest that countries with higher per capita GDPs tend to experience greater adoption of sustainable technologies like EVs, driven by increased financial capacity for investment. However, research remains limited in systematically evaluating and quantifying the link between per capita GDP and EV diffusion, particularly in the context of LCVs.

Exploring the role of economic factors in shaping EV adoption, research has also explored the association between the presence of automotive industries within the nation's economies and the accelerated diffusion of eLCVs. For example, Zimm (2021) argues that the presence and scale of a country's automotive sector positively influence EV diffusion. Their study identified passenger car manufacturing and an automotive producer binary variable as positive factors that influence the adoption of EV technology or facilitate policy implementation. These findings challenged Geels' argument that countries with large automotive industries are slower to transition to low-carbon systems due to resistance from incumbent industrial stakeholders (Geels 2019). In particular, Geels (2019) contended that industry actors actively safeguard their market positions, resisting policy reforms and hindering EV diffusion.

Simultaneously, several studies have stated that increased e-commerce has transformed goods purchasing and delivery practices, significantly impacting last-mile LCV activities (Allen et al. 2018; Anosike et al. 2021). Liu et al. (2022) showed that the increase in e-commerce influences the adoption of other eco-friendly practices, such as route optimisation and alternative fuel vehicles.

Various studies, including Christidis and Focas (2019), Matsumoto et al. (2021), Zimm, (2021) and Qin et al. (2022) have demonstrated a positive correlation between the impact of income per capita and the diffusion of EV or other sustainable technologies. In particular, Matsumoto et al. (2021) focused on the diffusion of hybrid electric vehicles (HEV) in Japan, revealing a noteworthy relationship between income per capita and HEV adoption. The study suggested that higher income levels facilitate increased diffusion of HEV. In contrast, Sierzchula et al. (2014) examined the influence of financial incentives and socioeconomic factors on EV adoption across 30 countries. They found that income per capita did not significantly predict EV market share. Instead, factors such as charging infrastructure, financial incentives, and the presence of local manufacturing facilities were more strongly associated with successful adoption in this study.

Several studies underscored the significant role of education levels in the diffusion process of innovations (Agan and Balcilar 2022; Foley et al. 2020; Matsumoto et al. 2021; Pasaoglu et al. 2016; Qin et al. 2022). In Agan and Balcilar's (2022) analysis of green technology diffusion, education was a crucial economic factor influencing technology diffusion. They found that higher education attainment positively influences individuals' perceptions and understanding of the environmental benefits of green technologies, including EVs (Agan and Balcilar 2022). This finding is consistent with other studies, such as Foley et al. (2020), which emphasise the relationship between higher education levels and EV uptake in regions like the Australian Capital Territory. Indeed, this study demonstrated that higher education levels empower individuals to make informed decisions about sustainable transportation options, thereby encouraging the adoption of EVs (Foley et al. 2020).

Differing viewpoints emerge regarding the relationship between urban dynamics and the diffusion of EVs. According to Zubaryeva et al. (2012) and Yang et al. (2023), a higher

proportion of the national population living in urban areas and increased population density can positively influence EV adoption. This positive influence was attributed to well-established charging infrastructure networks, higher income levels, and more substantial local incentives in urban areas than rural regions. Furthermore, in densely populated urban areas, the demand for efficient logistics and reliable charging infrastructure increases due to the higher volume of goods and services that must be transported. Yang et al. (2023) provided an example from Norway's passenger vehicle market, estimating that municipalities with a higher urban population tend to have higher EV adoption rates. In contrast, Fluchs (2020) argued that a lower proportion of the urban population results in a higher diffusion rate, suggesting a preference for EVs among individuals in rural or suburban areas.

Policies and governance variables

Different studies highlight the crucial role of financial incentives in promoting the diffusion of eLCVs (Bae et al. 2022; Costa et al. 2021; Denstadli and Julsrud 2019; Foley et al. 2020; Kalthaus and Sun 2021; Kaplan et al. 2016; Plötz et al. 2016). For instance, Plötz et al. (2016) utilised regression analysis to assess factors influencing plug-in electric vehicle adoption, emphasising the positive impact of financial incentives on sales shares in the US and eight EU countries. These incentives include direct and indirect measures, such as purchase subsidies and exemptions from transport or high-energy fossil fuel taxes. In China, Kalthaus and Sun (2021) demonstrated, using the generalised method of moments, that regional government subsidies contribute positively to the diffusion of EVs. Based on interviews with fleet operators, Bae et al. (2022) identified financial incentives as a pivotal factor driving the adoption of alternative fuel vehicles. Looking into EU countries' financial incentives, Gil Ribeiro and Silveira (2024) showed that while financial incentives have effectively reduced the initial cost barrier for electric LCVs in many countries, they have not yet guaranteed the overall cost-competitiveness of these vehicles in all countries. The results of this study also showed that financial incentives are crucial for achieving eLCV cost competitiveness compared to diesel LCV, but as currently designed, they are not optimised to fully support widespread diffusion. This study also found a small positive correlation between financial incentives and the share of electric LCVs in new registrations, suggesting that incentives partly explain eLCV diffusion and indicated the need for further investigation.

The diffusion of EVs may also be associated with a country's Research and Development (R&D) expenditures and innovation environment, as discussed by Fluchs (2020) and Jaiswal and Zane (2022). Jaiswal and Zane (2022) showed that R&D spending as a percentage of a nation's GDP, indicating the country's innovation focus, is an essential and sufficient factor for the diffusion of new technology (Jaiswal and Zane 2022). Fluchs (2020) investigated the innovation environment, captured through the Global Innovation Index. They found no statistically significant between this index and diffusion speed of battery EV in European countries, underscoring complex and sometimes indirect role that innovation plays in EV adoption trends.

Environmental and energy variables

CO₂ emission levels of a specific sector or country and the CO₂ intensity of electricity production are both factors that can significantly influence the diffusion of green technologies, specifically those related to eLCV. Agan and Balcilar (2022) found a positive and statistically significant impact of total national CO₂ emissions (aggregating all economic sectors) on the diffusion of sustainable technologies, particularly in countries with higher emissions levels. Their findings suggest that countries with greater environmental pressures may adopt green technologies as a response. Complementing this perspective, Zimm (2021) focused specifically on EV adoption and found that countries with lower CO₂ intensity in the electricity sector are more likely to adopt EVs. This implies that decreasing the proportion of high CO₂ emission energy sources, such as coal, in the electricity mix can foster the adoption of EVs, while enhancing efforts to mitigate climate change. These findings are not contradictory but complementary: while high overall emissions can act as a driver for policy interventions and technological transitions, lower carbon intensity in electricity generation strengthens the sustainability of EV adoption by ensuring that their use contributes more effectively to climate change mitigation. Seitz et al. (2015) developed a survey targeting organisations operating heavy-duty vehicles in Germany. They found that organisations with strong environmental attitudes and a commitment to corporate social responsibility are significantly more likely to adopt CO₂ saving vehicle technologies, highlighting the role of organisations' environmental awareness in driving the adoption of EV technology.

Künle and Minke (2022) found a positive correlation between the share of renewable energy in the electricity mix and EV adoption rates, suggesting that cleaner electricity generation may support the transition to electric mobility. However, Zubaryeva et al. (2012) reported no significant relationship between the share of renewable energy and EV adoption, highlighting the ongoing debate and complexity surrounding the role of electricity sources in influencing EV diffusion. In addition, various research papers investigated the relationship between energy costs and the market penetration of EVs (Pasaoglu et al. 2016; Sadeghian Esfahani et al. 2022; Zimm 2021), suggesting that lower electricity costs facilitate a higher diffusion of EVs. In addition, Sierzchula et al. (2014) suggested that energy cost fluctuations (including fossil fuel and electricity) can affect EV affordability and attractiveness, leading to variations in diffusion rates across different markets.

Zubaryeva et al. (2012) and Yang et al. (2023) investigated the impact of climatic conditions on EV diffusion, emphasising that factors such as low temperature can be a barrier to EV adoption, negatively impacting vehicle performance by reducing battery efficiency and driving range as the energy demands for battery heating and cabin conditioning increase. Further evidence is provided by Yang et al. (2023), who specifically found a positive correlation between minimum temperature and EV adoption, attributing this to the decreased performance of EVs in cold climates, as exemplified by Norway. Conversely, they observed no significant relationship between EV diffusion and factors such as wind speed and precipitation.

Transport and technology variables

While previous studies have drawn connections between transportation and technological factors, such as motorisation rates or the presence of charging stations, and the diffusion

of EVs in the passenger car sector, a noticeable gap remains in research regarding eLCV. Several studies, including those by Zubaryeva et al. (2012), Matsumoto et al. (2021), Zimm (2021), and Yang et al. (2023), have explored the connection between motorisation, driving behaviours, and EV diffusion. Matsumoto et al. (2021) found a significant positive correlation between the number of passenger cars and the ownership ratio of hybrid EVs. Similarly, Zimm (2021) supported the argument that the total number of passenger cars in a country positively influences the likelihood of EV uptake.

When assessing the diffusion of EVs for passenger cars, various factors are often cited, such as the total number of vehicles and the average annual mileage per vehicle (see Melander and Nyquist-Magnusson 2022, Saxena and Yadav 2023; Sonar et al. 2023). However, a notable gap emerges when the analysis is extended to eLCVs. Multiple researchers argue that the initial purchase price and the overall cost of vehicle ownership significantly influence the adoption and diffusion of EVs. For instance, Ahjum et al. (2018) emphasised that the vehicle purchase cost is the primary determinant of EV penetration into the vehicle stock. This study suggested that reducing the initial purchase price of EVs can enhance their appeal to consumers, thereby promoting diffusion. Skippon and Chappell (2019) and Galati et al. (2021), focusing on fleet adoption of plug-in vehicles, indicated that the cost of ownership remains a significant concern for fleet managers, underscoring the pivotal role of cost considerations in EV adoption.

Recent research highlights the positive influence of public charging infrastructure on the adoption and diffusion of EVs, particularly in the passenger car market segment (Foley et al. 2020; Liu et al. 2017; Yang et al. 2023; Zubaryeva et al. 2012). Yang et al. (2023) emphasised the importance of charging station availability in their in-depth analysis of Norway's mature EV market, particularly in addressing the challenges posed by cold climates. Similarly, Greene et al. (2020) emphasised the importance of the number of charging stations, their strategic placement, and their type for maximising EV adoption. Specifically, they found that intercity fast chargers are particularly valued by EV drivers, enhancing the perceived value and practicality of EVs. However, there is a gap in the existing literature regarding the relationship between the availability of public charging infrastructure and the diffusion of eLCVs.

Methods and materials

This section outlines the methodologies used to investigate and explore the factors influencing the diffusion of eLCVs. First, the research hypotheses, which form the analytical foundation, are presented. After the empirical models and respective testing processes are described, a description of dependent and independent variables and case studies follows. This methodology was constructed taking into consideration the exploratory nature of this research.

Hypotheses

The hypotheses are designed to investigate and validate the relationships between macro-environmental factors and the diffusion of eLCVs, this step is essential to the exploratory nature of the research, as it provides a structured basis for empirical analysis of the study.

The hypotheses are structured around four key typologies identified in the literature: socioeconomic conditions; policy and governance frameworks; environmental and energy-related factors; and transport and technological dimensions. Each typology forms the basis for a primary hypothesis, which seeks to capture the overarching relationship between these categories and eLCV adoption. The primary hypotheses are further disaggregated into sub-hypotheses, each targeting specific variables within the respective typologies to enable a more systematic and granular analysis. These sub-hypotheses reflect the core variables identified through the literature review and guide the subsequent empirical testing.

All hypotheses are formulated with an expected directional impact of each variable on the diffusion of eLCV, informed by insights from the literature review. In cases where prior research presents contradictory findings, the directional assumption follows the trend most commonly supported by existing studies, ensuring alignment with the broader empirical evidence. The panel regression model provides empirical validation, confirming or not confirming these specific directional conclusions regarding the determinants of eLCVs diffusion.

Hypothesis 1 *Socioeconomic variables impact the diffusion of eLCVs.*

Hypothesis 1 explores the impact of socioeconomic variables on the diffusion of eLCVs. Socioeconomic factors, such as economic output, population attributes, and urban density, are frequently linked to the diffusion of EVs. Previous studies suggest that variables such as GDP, education, and e-commerce drive EV adoption. However, limited research specifically addresses these variables in the context of eLCVs. To address this, the following sub-hypotheses are proposed:

- H1.1. GDP has a positive influence on the diffusion rate of eLCVs.
- H1.2. The existence of automotive industries has a positive influence on the diffusion rate of eLCVs.
- H1.3. E-commerce sales have a positive influence on the diffusion rate of eLCVs.
- H1.4. Population income has a positive influence on the diffusion rate of eLCVs.
- H1.5. Population education levels have a positive influence on the diffusion rate of eLCVs.
- H1.6. Population density has a positive influence on the diffusion rate of eLCVs.

Hypothesis 2 *Policies and governance variables impact the diffusion of eLCVs.*

Policies and governance mechanisms, including financial incentives and R&D investments, are critical drivers of EV diffusion. Despite existing research on passenger EVs, eLCVs remain understudied in this context. This study proposes the following:

- H2.1. Financial incentives for eLCVs have a positive influence on the diffusion rate of eLCVs.
- H2.2. R&D expenditures have a positive influence on the diffusion rate of eLCVs.

Hypothesis 3 *Environmental and energy variables impact the diffusion of eLCVs.*

Hypothesis 3 examines the impact of environmental and energy variables on eLCVs diffusion. Environmental factors such as CO₂ emissions, electricity costs, and renewable energy shares have been linked to EV adoption but lack focus in the eLCVs segment. This study extends the existing literature with the following sub-hypotheses:

- H3.1. CO₂ emissions from fuel combustion have a positive influence on the diffusion rate of eLCVs.
- H3.2. Electricity costs and fossil fuel costs have a positive influence on the diffusion rate of eLCVs.
- H3.3. Share of renewable energy in electricity has a positive influence on the diffusion rate of eLCVs.
- H3.4. Minimum temperatures have a positive influence on the diffusion rate of eLCVs.

Hypothesis 4: *Transport and technological variables impact the diffusion of eLCV.*

Hypothesis 4 investigates the influence of transport and technology variables on the diffusion of eLCVs. While previous studies have drawn connections between transportation and technological factors, such as motorisation rates or the presence of charging stations, and the diffusion of EVs in the passenger car sector, a gap exists in research regarding eLCVs.

Transport and technological attributes, such as motorisation rates, vehicle costs, and charging infrastructure, play a crucial role in EV diffusion. This study investigates these factors in the eLCVs context through the following hypotheses:

- H4.1. Motorisation rates have a positive influence on the diffusion rate of eLCVs.
- H4.2. Vehicle purchasing cost has a negative influence on the diffusion rate of eLCVs.
- H4.3. Availability of charging stations has a positive influence on the diffusion rate of eLCVs.

Table 1 synthesises four main hypotheses accompanied by 15 sub-hypotheses. These hypotheses collectively aim to identify the determinants that drive the diffusion of eLCVs.

Empirical models

Different panel data regression models are tested to evaluate various hypotheses and achieve the research objectives. Specifically, the statistical models tested are: Ordinary Least Squares Model (OLS), Least Squares Dummy Variables Model (LSDV), Fixed Effects Model (FEM), and Random Effects Model (REM). The equations of each statistical model are described in Appendix G. This methodological assessment seeks to determine the most appropriate panel data regression model, which most effectively captures the relationship between the dependent variable and 18 independent variables. Selecting the appropriate model ensures more reliable and accurate parameter estimates than alternative specifications. In essence, the chosen model best fits the data structure, accounting for individual heterogeneity and temporal effects, while delivering unbiased and efficient estimation.

The optimal panel data regression model is identified through a testing process that includes validation and diagnostic tests. The validation tests focus on model selection and are used to determine which model is more suitable for the data. More specifically, the

Table 1 Research hypotheses and sub-hypotheses

Typology	Hypotheses	Sub-hypotheses
Socioeconomic	Hypothesis 1. Socioeconomic variables impact the diffusion of eLCV	H1.1. GDP has a positive influence on the diffusion rate of eLCVs H1.2. The existence of automotive industries has a positive influence on the diffusion rate of eLCVs H1.3. E-commerce sales have a positive influence on the diffusion rate of eLCVs H1.4. Population income has a positive influence on the diffusion rate of eLCVs H1.5. Population education levels have a positive influence on the diffusion rate of eLCVs H1.6. Population density has a positive influence on the diffusion rate of eLCVs
Policies and governance	Hypothesis 2. Policies and Governance variables impact the diffusion of eLCV	H2.1. Financial incentives for eLCVs have a positive influence on the diffusion rate of eLCVs H2.2. R&D expenditures have a positive influence on the diffusion rate of eLCVs
Environmental and energy	Hypothesis 3. Environmental and energy variables impact the diffusion of eLCV	H3.1. CO ₂ emissions from fuel combustion have a positive influence on the diffusion rate of eLCVs H3.2. Electricity costs and fossil fuel costs have a positive influence on the diffusion rate of eLCVs H3.3. Share of renewable energy in electricity has a positive influence on the diffusion rate of eLCVs H3.4. Minimum temperatures have a positive influence on the diffusion rate of eLCVs
Transports and technological	Hypothesis 4. Transport and technology variables impact the diffusion of eLCV	H4.1. Motorisation rates have a positive influence on the diffusion rate of eLCVs H4.2. Vehicle purchasing cost has a negative influence on the diffusion rate of eLCVs H4.3. Availability of charging stations has a positive influence on the diffusion rate of eLCVs

F-test confirmed the adaptability/ inadaptability of the OLS model to the analysis (Croissant and Millo 2019) and the Hausman test was performed to reject or not the random-effects model in favour of the fixed-effects model (Clark and Linzer 2015). Hausman test detects if the results violate the random-effects modelling assumption that the explanatory variables are orthogonal to the unit effects (Clark and Linzer 2015; Hausman 1978). The diagnostic tests are conducted on the models to examine the robustness of the results and identify serial correlation and heteroscedasticity. More specifically, the research conducts the Breusch-Godfrey/Wooldridge test to assess serial correlation. Hypotheses are tested for no serial correlation in idiosyncratic errors (the hypothesis is rejected if p -value > 0.05). The Breusch-Pagan test is employed to identify heteroscedasticity. This test distinguishes heteroscedasticity as the alternative to the null hypothesis of homoscedasticity (the hypothesis is rejected if p -value > 0.05) (Breusch and Pagan 1979).

The research develops five data panel groups to investigate the hypotheses and sub-hypotheses outlined in Table 1. Research hypotheses and sub-hypotheses. The analysis includes a comprehensive and overall model (Group 5) that incorporates all variables across macro-environmental typologies to provide the most robust and unbiased estimates of factor effects. In addition, four supplementary models (Groups 1–4) are used as robustness checks, each focusing on a specific typology: Socioeconomic (Group 1), Policies and Governance (Group 2), Environmental and Energy (Group 3), and Transport and Technology (Group 4).

This approach enables a focused analysis concerning each macro-environmental typology area after examining the combined impact of all variables. By isolating the typologies, it is possible to have a clearer understanding of the contributions and dynamics of typologies and variables, which could be masked in a global model.

The hypotheses are confirmed based on the performance of panel data regression models corresponding to each hypothesis– macro-environmental typology group. Each hypothesis is linked to a specific panel data group, and a hypothesis is considered supported when the associated variable demonstrates a statistically significant effect (typically $p < 0.05$) and aligns with the expected direction. Adjusted R-squared values are reported as supplementary indicators of overall model fit, reflecting the proportion of variance in the diffusion variable explained by the group's variables.

The validation of the sub-hypotheses is connected to the impact of independent variables within the overall model (Group 5). Each hypothesis is tested by examining the statistical significance (p -values), direction, and magnitude of the corresponding variable's coefficient within the comprehensive model (Group 5). The statistical significance and influence of each variable in the global model offer valuable insights into how various factors contribute to the overall diffusion process. The independent variable is considered statistically relevant at the 5% significance level when the p -value is lower than 0.05 (Andrade 2019). A p -value lower than 0.05 provides statistical evidence sufficient to suggest that the independent variable is significantly associated with the dependent variable, providing evidence of its influence on the outcome in the model context. This approach supports the identification of critical variables for empirical models. A sub-hypothesis is confirmed if the related variable significantly influences eLCVs diffusion, and partially confirmed if only some related variables are significant.

The different panel data regression models are tested for each data panel group with the open-source software environment “R” (using the package `plm`). This software and package provide the functionalities needed for the econometric analysis of the data panels (Croissant and Millo 2008).

Dependent variable

The dependent variable is the share of electric vehicle sales in the LCV market and represents the diffusion of eLCVs. The size of LCV markets differ across countries, so this percentage allowed a consistent cross-country analysis. The dependent variable data is collected from the registration of electric vehicle data of the European Alternative Fuels Observatory (EAFO) and includes information between 2010 and 2022.

This variable presents an unequal distribution between countries, as seen in Figs. D1 and D3 in Appendix D. It varies between zero and a maximum of 14% (in Sweden), an average of 0.7% (standard deviation of 1.5%), and the skewness value is approximately 4 (to the right). Consequently, this variable is normalised with a square root transformation to get better prediction results and reduced heteroscedasticity of the residuals in linear regression (Field 2018; Gelman and Hill 2007). After the square-foot transformation, a second histogram showed that EV sales share is closer to a normal distribution (see Appendix D, Figures D2 and D4), validating this approach. Ultimately, the square root of EV sales share is used as the primary dependent variable in developing and analysing the empirical model.

Independent variables

The selection of the variables considers (1) variables identified in the literature and related to the typologies identified, (2) the relation to LCVs, (3) the data availability for the 2010–2022 period, and (4) the simplification of the model, focusing on avoiding duplication, high correlation and collinearity. Indeed, correlation tests are performed between independent variables, and the final variable list is set to reduce high correlation and collinearity. Although the study is structured around 16 hypotheses, 18 independent variables are included in the analysis, as some hypotheses are examined using multiple variables. The results of the correlation analysis are presented in Appendix F, Table F1. The following variables were excluded from this process: population income, level of internet access, number of assembly and production vehicle plants per country, energy taxes, transport taxes, private expenditure accounted for by gross domestic expenditure on R&D, and annual growth in road transport energy demand. As a result of this analysis, the hypothesis related to population income (H.1.4) could not be tested in the model and was therefore not included in the further analysis.

The data for each variable is retrieved from different sources described in Appendix E, including observations and assumptions related to missing values. The investigation of Hypothesis 1 focuses on socioeconomic variables encompassing economic conditions, population dynamics, and urban areas (see Table 2).

The policies and governance group models are developed to test Hypothesis 2, which includes four variables related to regulation, policy instruments, and the investment and R&D environment (see Table 3). Regarding policy instruments, this research reviews financial incentives for all case countries between 2010 and 2022, focusing on eLCVs. In 27 European countries, this study identified three main groups of financial incentives used as policy measures to encourage the adoption of EVs. These incentives are linked to the purchase and ownership of EVs: (a) direct incentives, which include direct monetary support upon the purchase of an EV (direct/one-time); (b) indirect incentives, tax benefits, such as fees and tax reductions or exemptions, that applied in different stages of ownership (indirect/one time or recurring/annually); (c) and combined schemes, where direct and indirect incentives are combined as a single instrument. These incentives were integrated into the empirical models using the value of direct subsidy (Dsubsidy) and the electric vehicle tax reduction or exemption (TaxExem) variables.

The investment and R&D environment components are integrated into the models by two variables covering R&D expenditures. Public expenditures are measured with the Government budget allocations for the R&D variable (PubExp), which comprises the share of government budget allocations for R&D in total general government expenditure.

This study incorporates five variables within the models to assess the impact of environmental and energy factors on the diffusion of eLCVs and testing Hypothesis 3 (see Table 4). More specifically, with a direct link to environment and sustainability, the empirical model includes CO₂ emission from LCV (LCVemi) and the Share of Energy from renewable sources in electricity (ShareEn). Additionally, when examining the energy system, particular attention is dedicated to the prices of electricity and diesel (ElPrice and DiPrice). The climatic conditions are represented in the model by the average minimum temperature variable (MinTemp).

Table 2 Descriptive statistics of socioeconomic variables (2010–2022)

Sub-hypothesis	Abbreviation	Variable	Definition	Unit of measure	Minimum	Maximum	Mean	SD
H1.1	GDP	Main GDP aggregates per capita	Gross domestic product at market prices	Purchasing power standard per capita	8963.2	44,097.3	20,611.2	6091.3
H1.2	LCVprod	Number of LCVs produced per country	Number of LCVs produced per country	Number of vehicles	0	640,117	63,514	142,381
H1.3	Ecom	Value of e-commerce sales	Value of e-commerce sales from all enterprises, without the financial sector	Percentage of turnover	1.3	44.0	15.7	7.7
H1.5	Edu	Tertiary educational attainment	Percentage of the population aged 25–64 who have completed tertiary studies	Percentage of the population aged 25–64	20.7	62.6	39.8	9.5
H1.6	PopDen	Population density	The ratio between the annual average population and the land area	Persons per square kilometre	18	1657	176	275

Hypothesis H.1.4 was not tested due to high correlation with other variables identified during the preliminary correlation analysis. Consequently, the associated variable was excluded from the model, and the hypothesis is not included in this table

At last, for testing Hypotheses 4, concerning the transport and technology, the models include five variables systematised in Table 5: Motorisation rate (MOTrate) and LCV rate (LCVrate), assessing the ratio of different types of vehicles per 1000 inhabitants; the purchasing power parities for transports equipment (PPPTrans), to include the variation in vehicle price across countries; and the total number of charging connectors (Recharg).

Sample: case study countries

All EU countries are considered in the regression analysis to test the hypotheses: Austria, Belgium, Bulgaria, Croatia, Cyprus, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, and Sweden. Similarities and differences were identified, analysed, and explained across 27 countries, considering the data collection protocol presented in Appendix E. This cross-country study aims to identify key factors linked to the diffusion of electric Light Commercial Vehicles between 2010 and 2022.

Results

This section presents the panel data regression analysis results, considering the four-panel data regression models and five variable groups described in the previous section. It is important to note that groups 1–4 correspond to the four main hypothesis tests, while group 5 models are used to test the sub-hypotheses. Table 6 outlines the outcomes of comparing various statistical models, revealing that the LSDV Model yields a superior fit with an elevated adjusted R^2 value of 0.81 for group 5 variables. This improvement is attributed to the LSDV model's incorporation of distinct coefficients for individual countries, resulting in unique equations for each country. However, this research opted for the FEM due to its capacity as a mathematical model that concurrently controls for both country and time effects. With FEM estimates within-country variations over time while removing cross-country differences through demeaning or differencing, this allows to control for unobservable factors that vary across countries and over time. This approach helps prevent biased estimates by accounting for unobserved heterogeneity that could otherwise confound the results.

Additionally, the findings underscore the higher model fit for the FEM analysis, yielding higher R^2 values by acknowledging that variables remain constant across entities/countries but vary over time. Corroborating these findings, the F -test proved the inadaptability of the OLS model for all the equations (P -value $< 2.2e-16$). Moreover, the Hausman test consistently favoured the fixed-effects model over the random-effects model, rejecting the latter in all instances (P -value $< 2.2e-16$), except for model 2. Despite this exception, the overall superiority of employing the fixed-effects model remains evident for most equations in the analysis.

The serial correlation and heteroskedasticity test results indicated significant evidence against the null hypothesis. Consequently, model estimators were corrected using the Arellano method to address the dataset's potential issues related to heteroskedasticity and serial correlation (Arellano and Bond 1991; Shobande and Ogbeifun 2022). Furthermore, it is

Table 3 Descriptive statistics of policies and governance variables (2010–2022)

Sub-hypothesis	Abbreviations	Variable	Definition	Unit of measure	Minimum	Maximum	Mean	SD
H2.1	Dsubsidy	Value of the direct subsidy	Value of direct subsidy given to electric vehicle upon purchase	Euro	0	20,000	1695	2997
H2.1	TaxExem	Electric vehicle tax reduction or exemption	Identification of tax reduction or exemption for EVs, considering registration taxes and ownership/circulation taxes	Yes/no	0	1	0.42	0.50
H2.2	PubExp	Government budget allocations for R&D	Share of government budget allocations for R&D in total general government expenditure	Percentage of government expenditure	0.3	2.2	1.2	0.4

important to acknowledge the limitations of the R-square of the FEM model in the context of time series analysis. Although R^2 provides an indication of the overall model fit, its interpretation in the FEM model requires caution. The primary focus in this model is on the statistical significance of individual coefficients, which are critical for validating the sub-hypotheses.

Table 7 presents estimations obtained from FEM following corrections with Arellano estimators. The results reveal two key findings (Arellano 1987). The variables that are statistically significant in the global model are highlighted in bold.

Firstly, among the 18 identified variables, eight exhibit significant effects on the share of eLCVs registrations, indicating that eight hypotheses can be confirmed (see Table 8) at a 5% significance level and are described in the next section (**Socioeconomic variables (Hypothesis 1)**–**Transport and technology variables (Hypothesis 4)**). These variables are: GDP, e-commerce sales, population density, fossil fuel prices, the share of energy from renewable sources in electricity, motorisation rate, transport equipment PPPs and the number of charging stations. Secondly, most of the eight variables positively impact the share of eLCVs in the total number of registrations, indicating that an increase in the variable values corresponds to a rise in eLCV diffusion.

Socioeconomic variables (Hypothesis 1)

The estimations of the socioeconomic group (Group 1) show an adjusted R-square value of 0.60 in the FEM, indicating that socioeconomic variables explain a substantial portion of diffusion variation and effectively capture underlying changes. The socioeconomic model demonstrated the best fit compared to the other three typologies.

This model highlights several socioeconomic factors influencing the share of new eLCVs registrations. Population density has a high statistical significance, positively increasing the share of new registrations for eLCVs. The GDP per capita also exhibits statistical significance, emphasising its substantial role in shaping the diffusion of eLCVs. The total turnover from e-commerce sales by enterprises exhibits a statistically significant effect in the model, with lower statistical significance (4%), highlighting the role of e-commerce activities associated with the rise of eLCVs registrations. On the other hand, the number of LCVs produced per country and tertiary educational attainment did not demonstrate statistically significant effects on the share of new eLCVs registrations, with p-values exceeding 0.05. Therefore, in this model, these variables are not statistically significant and do not appear to have a measurable influence on the diffusion of eLCVs.

Policies and governance variables (Hypothesis 2)

The Policies and Governance group exhibits a better fit when employing the random effects regression model, as evidenced by the results of the Hausman test (P -value > 0.05 , as presented in Table 7). This result suggests that the random effects regression is a more appropriate choice for group 2, indicating that including random effects better accommodates the underlying structure of the data than FE regression. In random effects regression, the estimated individual effect (α) is a random variable uncorrelated with the explanatory variables (Schmidheiny 2021). Conversely, even with random effects regression, this Policy and government model proved insufficient to explain the diffusion variation (adjusted R^2 is

Table 4 Descriptive statistics of environmental and energy variables (2010–2022)

Sub-hypothesis	Abbreviations	Variable	Definition	Unit of measure	Minimum	Maximum	Mean	SD
H3.1	LCVemi	CO ₂ emissions from LCV	CO ₂ emissions by Fuel combustion in LCV	Thousand tonnes	66.9	19,810.2	3122.7	4279.4
H3.2	ElPrice	Electricity prices for Non-household	Average national price in Euro per kWh without taxes	Euros per kWh	0.05	0.28	0.10	0.03
H3.2	DiPrice	Diesel price per litre	Yearly average diesel price with all taxes per country	Euros per litre	0.9	2.3	1.3	0.2
H3.3	ShareEn	Share of energy from renewable sources in electricity	Share of energy from renewable sources in electricity	Percentage	0.0	78.3	29.1	18.7
H3.4	MinTemp	Average minimum temperature	Annual Average Minimum Surface Air Temperature	Degrees Celsius	-2.3	19.2	7.3	4.2

0.35). These results suggest that even with the more flexible framework provided by random effects, the model 2 explanatory power remains limited in capturing the complexities of the diffusion process. Notably, this result underscores the limited explanatory power of this variables group and highlights the complexities of the diffusion process, which may require additional or alternative variables for better understanding.

Upon examining the global model, it becomes evident that Policies and Governance variables do not demonstrate statistical significance, as their p -values exceed the conventional threshold of 0.05. This suggests that these variables contribute insufficiently to explaining the diffusion of eLCVs.

Environmental and energy variables (Hypothesis 3)

FEM regressions were found to be the most appropriate specification for the Environmental and Energy variables group. The selected independent variables account for a substantial proportion of the variation in the share of electric vehicles among newly registered light commercial vehicles, as reflected by an adjusted R^2 value of 0.58. Within the group 5 model, two explanatory variables demonstrated statistically significant impacts on the diffusion of eLCV. Notably, the estimated coefficient for the share of renewable electricity sources is positive and highly statistically significant ($p < 0.001$).

The variable representing Diesel prices showed a positive relationship with the dependent variable and is also highly statistically significant ($p < 0.001$). This finding suggests that an increase in diesel prices is associated with the diffusion of eLCV. In contrast, the electricity prices variable is not statistically significant. Consequently, Hypothesis H3.2 is partially confirmed, as only one of the two variables tested demonstrated statistical significance.

In contrast, the variables representing CO_2 emissions from LCV, electricity prices for non-household consumers, and average minimum temperature did not exhibit statistically significant effects on the share of new eLCV registrations, with p -values exceeding 0.05. Accordingly, in the Group 5 model, these variables were neither statistically significant nor demonstrated any discernible influence on the diffusion of eLCVs.

Transport and technology variables (Hypothesis 4)

The transport and technology group explains a small portion of the dependent variable, revealing a relatively low adjusted R^2 of 0.39. However, the group 5 model shows three independent variables that significantly influence the diffusion of eLCVs. Indeed, PPPs for transport equipment have statistical significance, demonstrating a positive influence on the dependent variable. These results suggest that countries with higher economic capacity, reflected in elevated PPPs for transport equipment, experience a substantial surge in the proportion of eLCVs in the overall registrations. The motorisation rate also emerges as a statistically significant variable, displaying a negative coefficient of -0.00121 . This inverse relationship suggests that lower motorisation levels are associated with a higher share of eLCVs, potentially reflecting market conditions in which less motorised countries are more responsive to adopting eLCVs. However, this effect may also be influenced by unobserved variables not captured within the current model, highlighting the need for further investigation to understand the underlying drivers better. Additionally, the total number of charging

Table 5 Descriptive statistics of transport and technology variables (2010–2022)

Sub-hypothesis	Abbr	Variable	Definition	Unit of measure	Minimum	Maximum	Mean	SD
H4.1	MOTrate	Motorisation rate	Passenger cars per 1000 inhabitants	Number	18	1657	470	152
H4.1	LCVrate	LCVs rate	LCV per 1000 habitants	Number	1	265	59	27
H4.2	PPPTrans	Purchasing power parities for transport's equipment	Purchasing power parities (PPP), price level indices and real expenditures for ESA 2010 aggregates	Purchasing power parities	0.8	367.1	13.2	53.3
H4.3	Recharg	Total number of charging connectors	Total number of recharging connectors	Number	0	113,713	4392	12,784

connectors is statistically significant, indicating that greater charging infrastructure availability may positively influence the diffusion of eLCVs.

Table 8 summarises the findings across all variables. Hypotheses were assessed based on the statistical significance of the relevant variables in each group model and the model's explanatory power (adjusted R^2). A hypothesis was confirmed when most sub-hypotheses yielded significant results, and the model explained a substantial share of the variation in eLCVs diffusion. Specifically, a positive association is identified between socioeconomic variables and the diffusion of eLCVs (H1), with statistical significance observed for at least one variable under this hypothesis. At the same time, environmental and energy variables also significantly influence the diffusion of eLCVs (H3). Models 1 and 3 are statistically significant and explain some of the variation in the diffusion of eLCVs. Some sub-hypotheses were also confirmed (H1.1; H1.3; H1.6; H3.3; H4.2; H4.3).

The hypotheses were partially confirmed when only some sub-hypotheses were significant or the model's explanatory power was relatively low (H5). Hypotheses were not confirmed when none of the variables were important, and not tested when a variable was excluded due to methodological reasons such as multicollinearity.

Discussion

This exploratory study employed a range of panel data regression models to identify the statistical approach that best captures the dynamics of the phenomenon under investigation. The FEM approach was selected as the most appropriate specification for examining the macro-environmental determinants of eLCV diffusion across EU member states. It was subsequently used to test the proposed hypotheses. The FEM approach reveals patterns and influential relations between the independent and dependent variables, identifying key variables that justify the divergences linked to the share of eLCVs across EU countries. The FEM model indicates how changes in the independent variables within each entity over time influence the dependent variable while accounting for unobserved, time-invariant factors unique to each entity. This approach highlights the significance of within-entity dynamics and controls for omitted variables that could bias the results. It is also important to emphasise that no single variable alone significantly contributes to the diffusion of eLCVs, and the sub-hypotheses only hold meaning as integral components of the analytical framework.

The hypothesis testing key findings are the confirmation of seven in a total range of 16 sub-hypotheses and can be summarised as follows:

- (1) The results indicate a statistically significant positive relationship between socioeconomic variables and eLCVs diffusion, confirming Hypothesis 1. Notably, the socioeconomic model demonstrated the best fit compared to the other three typologies, reinforcing the roles of GDP, e-commerce, and population density as key drivers of eLCV adoption. These results highlight the importance of integrating these variables into forecasting models and policy frameworks to accelerate electric LCV adoption, particularly in urban and economically developed regions.

More specifically, in line with the literature's focus on other technologies, the results indicate that Countries with higher GDP have higher eLCVs diffusion rates, confirming H1.1. This suggests that economic prosperity impacts eLCVs diffusion and is often

Table 6 Statistical models diagnoses and test results

Panel data model	Evaluation metrics		Group 1		Group 2		Group 3		Group 4		Group 5-Global model	
			Socioeconomic		Policies and governance		Environmental and energy		Transport and technology		Global	
Ordinary least squares	Adjusted R ²		0.3839		0.3885		0.3389		0.3983		0.7302	
	P-value		<2.2e-16		<2.2e-16		<2.2e-16		<2.2e-16		<2.2e-16	
Least squares Dummy Variables	Adjusted R ²		0.7066		0.4588		0.6878		0.5469		0.8118	
	P-value		<2.2e-16		<2.2e-16		<2.2e-16		<2.2e-16		<2.2e-16	
Fixed effects (using plm)	Adjusted R ²		0.60543		0.27222		0.58014		0.39073		0.74694	
	P-value		<2.2e-16		<2.2e-16		<2.2e-16		<2.2e-16		<2.2e-16	
Random effects (using plm)	Adjusted R ²		0.46089		0.35007		0.44146		0.41047		0.7195	
	P-value		<2.2e-16		<2.2e-16		<2.2e-16		<2.2e-16		<2.2e-16	
<i>Validation and diagnoses tests</i>												
F-Test	P-value		<2.2e-16		2.07E-05		<2.2e-16		4.949E-14		<2.2e-16	
			<2.2e-16		0.7203		<2.2e-16		0.00002552		<2.2e-16	
Hausman test	P-value		1.09E-14		<2.2e-16		3.29E-15		<2.2e-16		5.34E-11	
			2.56E-12		1.38e-08		6.45E-07		3.81E-05		2.19E-12	
Serial correlation test	P-value											
Heteroskedasticity test	P-value											

used when modelling the diffusion of eLCVs. However, the results indicate that GDP alone, which some researchers have used, cannot fully predict the evolution of EVs.

The results further indicate that higher percentages of e-commerce sales may positively impact the diffusion rates of eLCVs, confirming the impacts of e-commerce on the LCVs' activities. These results align with Liu et al. (2022) those who link the growth of e-commerce to the adoption of eco-friendly practices. Driven by a growing demand for sustainable transportation alternatives and environmentally conscious practices, this trend can also be sustained by the potential for economies of scale.

The results indicate that population density may positively impact the diffusion rates of eLCVs (H1.6). This information echoes the findings that support the perspectives of Yang et al. (2023) and Zubaryeva et al. (2012), which are linked to the positive effect of high population density on EV adoption. Population density is crucial to establishing a logistics and charging network, influencing eLCVs' adoption.

- (2) The findings demonstrate that environmental and energy variables may impact the adoption of eLCVs, confirming Hypothesis 3. Specifically, this correlation is observed in variables such as fossil fuel costs and the share of energy from renewable sources in electricity.

Our results demonstrate that higher fossil fuel costs can result in higher diffusion rates of eLCVs (H3.2), indicating a positive influence, which is in line with the findings by Zimm (2021). Moreover, the findings suggest that owners of LCVs may exhibit a greater inclination towards embracing EVs as an alternative to conventional fuel-powered counterparts, particularly in the face of higher fossil fuel costs. Notably, this study did not confirm the impact of electricity prices on the diffusion of eLCVs, implying that these may exert a comparatively lesser influence on EV adoption when compared to fossil fuel prices, potentially due to the immediate visibility and volatility of fossil fuel costs, which significantly impact operational budgets. Moreover, in contrast, electricity prices tend to be more stable and predictable, especially if owners benefit from fixed-rate charging or subsidies. Consequently, policies aimed at accelerating the adoption of eLCVs should focus on amplifying the cost advantage of EVs over traditional fuel-powered vehicles, such as increasing fossil fuel taxes or enhancing financial incentives for EV charging.

Additionally, promoting greater transparent electricity costs and stabilising them through investment in renewable energy and grid efficiency could further reduce adoption barriers. Furthermore, the relative price differential between fossil fuel and electricity costs may also play a crucial role in influencing eLCV adoption. Future studies could investigate how variations in this energy price differential, across countries and over time, affect the cost competitiveness of eLCVs, offering insights into how energy pricing policies and market trends shape EV adoption behaviour.

Additionally, the analysis reveals that the proportion of renewable sources in electricity generation is associated with the rates of eLCVs diffusion (H3.3). This highlights the significance of renewable energy sources in fostering the widespread adoption of eLCVs, corroborating the findings by Künle and Minke (2022). Their found that greater use of renewable energy in the electricity supply encourages adoption of eLCVs, as show increased interest in reducing their carbon footprint. Our findings also align with Kunze et al.'s results, who found that the renewable share in EV charging often exceeds the average of national electricity mix (Kunze et al. 2024). Specifically, Kunze et al.

Table 7 Results of panel data analysis of the global model using fixed-effect regression

Typology	Sub-hypotheses	Acronym	Variable	Coefficient	Pr(> t)	Std. Error	T value
Socioeconomic	H1.1	GDP	Main GDP aggregates per capita	5.96E-05	0.003**	1.99E-05	2.996
	H1.2	LCVprod	Number of LCVs produced per country	1.27E-07	0.753	4.04E-07	0.315
	H1.3	Ecom	Enterprises' total turnover from e-commerce sales	0.017	0.040*	8.48E-03	2.060
	H1.5	Edu	Tertiary educational attainment	0.014	0.059	0.007	1.899
	H1.6	PopDen	Population density	3.52E-03	<2.2e-16***	3.97E-04	8.877
Policies and Governance	H2.1	Dsubsidy	Value of the direct subsidy	1.43E-05	0.100	8.66E-06	1.651
	H2.1	TaxExem	Electric vehicle tax reduction or exemption	0.010	0.874	0.060	0.159
Environmental and Energy	H2.2	PubExp	Government budget allocations for R&D	-0.146	0.155	0.102	-1.427
	H3.1	LCVemi	CO ₂ emission from LCVs	3.85E-05	0.090	2.27E-05	1.699
	H3.2	EIPrice	Electricity prices for non-household	-2.58E+00	0.065	1.39E+00	-1.852
	H3.2	DiPrice	Average of Diesel price in euros (IL)	0.363	0.004**	0.125	2.902
	H3.3	ShareEn	Share of energy from renewable sources in electricity	0.022	0.001**	0.007	3.235
Transport and technology	H3.4	MinTemp	Average minimum temperature	-0.030	0.388	0.035	-0.865
	H4.1	MOTrate	Motorisation rate	-1.21E-03	3.87E-08***	2.15E-04	-5.640
	H4.1	LCVrate	LCV's rate	4.53E-04	0.613	8.97E-04	0.506
	H4.3	PPPTrans	Purchasing power parities for transports equipment	7.04E-03	<2.2e-16***	5.16E-04	13.640
H4.4	Recharg	Total number of charging connectors	1.12E-05	3.19E-04***	3.07E-06	3.641	

The independent variable is considered statistically relevant at the 5% significance level when the *p*-value is lower than 0.05 (Andrade 2019)

p*<0.05, *p*<0.01, ****p*<0.001

(2024) report that contracted renewable electricity accounted for 57–66% of EV charging in Europe in 2022, compared to 49% in the total electricity mix.

The present study findings may suggest that policy measures and market incentives promoting renewable energy positively influence eLCVs' diffusion. While this relationship was not directly examined in the analysis, these findings aligned with the literature and indicate an interconnectedness between energy and transport policies in driving the transition towards low-carbon transportation, illustrating a coupling between the energy and transport sectors (Kunze et al. 2024). However, further investigation is needed to better understand the importance of aligning energy and transport policies when supporting the widespread adoption of eLCVs.

- (3) Transport and technology variables can be crucial in predicting and estimating the diffusion of eLCVs. The availability of charging stations positively impacts the diffusion of eLCVs (H4.3), aligning with findings from various authors focused on other vehicle categories, such as passenger cars. Indeed, countries with higher charging station availability have higher diffusion rates. This result has a dual interpretation. On the one hand, it emphasises the crucial role of developing a robust and extensive charging infrastructure to support and stimulate the diffusion of eLCVs. It highlights the necessity for supportive policies, investments in infrastructure expansion and new business models. On the other hand, this positive correlation may reflect the interplay between the development of charging infrastructure and market demand.

As the eLCVs market expands, the growth of charging infrastructures becomes a market response to meet the escalating demand. Therefore, this discussion revolves around a 'chicken and egg' dilemma akin to the interdependence of charging infrastructure deployment and the adoption of EVs: each supports and influences the other reciprocally (Luo et al. 2023; Shi et al. 2021; Zink et al. 2020). Analysing this dilemma regarding eLCVs is crucial to understanding this mutual influence when designing government policies and business models.

The findings also indicate a strong correlation between a country's economic capacity, as reflected in higher transport equipment PPPs and the increased diffusion of eLCVs (H4.2). Notably, purchasing power parities significantly positively impact the dependent variable. This result is consistent with previous research that emphasises the primary role of vehicle cost in EV penetration (Ahjum et al. 2018; Fluchs 2020; Galati et al. 2021; Künle and Minke 2022), identifying this variable as a primary explanatory determinant.

- (4) Policies and Governance variables did not demonstrate statistical significance in the empirical models. Consequently, it was impossible to prove a relationship between them and explain the EVs' share in newly registered LCVs. Therefore, Hypothesis 2 was not confirmed.

It is crucial to consider possible reasons for this outcome, such as limitations in the dataset, measurement issues with the variables, and contextual factors influencing the relationship between policies and governance variables and eLCVs diffusion. For instance, this finding may suggest that current policies and governance variables have a minimal effect on the spread of eLCV and are surpassed by other factors such as cost-effectiveness, operational efficiency, and business practices required in the decision-making process for LCVs primarily owned by companies (Skippon and Chappell 2019). Consequently, these vehicles' adoption rates may not strongly respond, for example, to policy

Table 8 Summary of findings: hypothesis testing results

Typology	Sub-hypotheses	Operationalisation variable	Results
Socioeconomic	Hypothesis 1. Socioeconomic variables impact the diffusion of eLCVs		Confirmed
	H1.1. GDP has a positive influence on the diffusion rate of eLCVs	Main GDP aggregates per capita	Confirmed
	H1.2. The existence of automotive industries has a positive influence on the diffusion rate of eLCVs	Number of LCVs produced per country	Not confirmed
	H1.3. E-commerce sales have a positive influence on the diffusion rate of eLCVs	Enterprises' total turnover from e-commerce sales	Confirmed
	H1.4. Population income has a positive influence on the diffusion rate of eLCVs	Population income	Not tested
	H1.5. Population education levels have a positive influence on the diffusion rate of eLCVs	Tertiary educational attainment	Not confirmed
Policies and governance	H1.6. Population density has a positive influence on the diffusion rate of eLCVs	Population density	Confirmed
	Hypothesis 2. Policies and Governance variables impact the diffusion of eLCVs		Not confirmed
	H2.1. Financial incentives for eLCVs have a positive influence on the diffusion rate of eLCVs	Value of the direct subsidy and Electric vehicle tax reduction or exemption	Not confirmed
	H2.2. R&D expenditures have a positive influence on the diffusion rate of eLCVs	Government budget allocations for R&D	Not confirmed
Environmental and energy	Hypothesis 3. Environmental and energy variables impact the diffusion of eLCVs		Confirmed
	H3.1. CO ₂ emissions from fuel combustion have a positive influence on the diffusion rate of eLCVs	CO ₂ emissions from LCVs	Not confirmed
	H3.2. Electricity costs and fossil fuel costs have a positive influence on the diffusion rate of eLCVs	Electricity prices for Non-household and Average Diesel price in euros (1L)	Partially confirmed
	H3.3. Share of renewable energy in electricity has a positive influence on the diffusion rate of eLCVs	Share of energy from renewable sources in electricity	Confirmed
Transports and infrastructures	H3.4. Minimum temperatures have a positive influence on the diffusion rate of eLCVs	Average minimum temperature	Not confirmed
	Hypothesis 4. Transport and technology variables impact the diffusion of eLCVs		Partially confirmed
	H4.1. Motorisation rates have a positive influence on the diffusion rate of eLCVs	Motorisation rate	Partially confirmed
	H4.2. Vehicle purchasing cost has a negative influence on the diffusion rate of eLCVs	LCVs rate	Partially confirmed
	H4.3. Availability of charging stations has a positive influence on the diffusion rate of eLCVs	Purchasing power parities for transport equipment Total number of charging stations	Confirmed

incentives, as already shown by some authors. Gil Ribeiro and Silveira (2024) show that existing policies are not always contributing to making eLCVs cost-competitive and that higher vehicle incentives do not represent higher diffusion rates. In addition, several studies (Bae et al. 2022; Kalthaus and Sun 2021; Plötz et al. 2016) have highlighted the positive impact of financial incentives on EV diffusion, though many do not quantify this effect. The relatively weaker correlation observed in the present study may be attributed to differences in study design, geographic and temporal scope, as well as the inclusion of additional variables that more comprehensively capture the complex and multifaceted nature of eLCV adoption.

Also, while the examined policies in the present study did not have a statistically significant impact, other government measures not considered in this analysis may play a crucial role in the diffusion of electric LCVs. These measures may include investments in charging infrastructure, urban access regulations, or incentives for renewable energy electricity generation. Further research is needed to investigate the causality between policies, governance, and the diffusion of eLCVs.

Aligned with existing literature, the model analysis confirms that the diffusion of EVs is a multifaceted phenomenon, similar to the diffusion patterns observed in the diffusion of other innovations. This underscores the inefficiency of focusing solely on a single macro-environmental typology.

This research provides valuable insights into the diffusion of eLCVs within the EU, but certain limitations should be acknowledged. First, the reliance on available data limits the analysis due to the potential for bias. This bias arises from excluding certain aspects of the phenomenon under investigation, which may limit the comprehensiveness of the findings. To overcome this constraint, efforts were made to incorporate various types of variables from different data sources, thereby enhancing the robustness and inclusivity of the approach. Future research should investigate less quantifiable factors, such as the impact of environmental awareness on shaping policy decisions and the dynamics of the transportation market. Specifically, examining variations in environmental consciousness across countries could provide insights into its influence on adopting eLCVs. Understanding this relationship could help determine whether environmental awareness is a fundamental driver of policy support and market electrification. Second, the focus of this study on macro-environmental variables could be seen as a limitation, as it may neglect relevant micro-environment variables influencing the diffusion of eLCVs, like specific regional or city-level policies, such as low-emission zones and fees or specific subsidies, and specific market dynamics related to the freight transportation sector, such as customer preferences and behaviours. A comprehensive examination of these omitted micro-environment variables could yield valuable additional insights and represent an important direction for future research. Third, this study does not explicitly consider the potential impact of disruptive external events, such as economic and public health crises or geopolitical events. These limitations underscore the need for further research to thoroughly investigate how unforeseen external shocks may impact the diffusion of eLCVs. Fourth, the geographic scope of the study, limited to the EU, may constrain the generalizability of the findings to other regions or global contexts. Expanding the scope of future studies to include non-EU regions or a broader international perspective could enhance the applicability and relevance of the findings to a wider audience. Fifth, while this analysis incorporates temporal and cross-country variation in the nominal value

of financial incentives, specific relative variables could be included to improve the accuracy of the analysis, such as incentives expressed as a percentage of the vehicle cost. However, collecting consistent and comparable vehicle pricing data across countries and over time presents significant challenges, given the variation in models, configurations, tax regimes, and market conditions.

Future research with access to such detailed data could further refine the understanding of how incentive design influences eLCV adoption. Sixth, defining four group models for each typology has limitations due to the oversimplification of variable relationships. Isolating typologies may overlook important interactions, leading to an incomplete understanding of factors influencing eLCVs' penetration rates. However, this approach is justified as it systematically analyses the individual contributions of each typology, which is essential for hypothesis testing. At last, the analysis of FEM did not provide a comprehensive overview of country-specific conditions. Exploring disparities among different groups of countries, such as by region or economic classification, can provide valuable insights. Future analyses could improve this approach by grouping countries into relevant clusters and examining the variations in adoption patterns within these clusters.

Conclusions

This study contributes to the literature by offering EU-wide insights into the determinants of eLCV diffusion, expanding prior research that mainly focused on passenger vehicles or country-specific factors. By using an exploratory methodology, it introduces a broader set of explanatory variables relevant to low-carbon technology diffusion. It demonstrates that a fixed-effects panel data regression model can effectively capture the variation in eLCV adoption across the EU, with an adjusted R-squared value of 0.75. The analysis highlights seven key factors: GDP, e-commerce sales, population density, fossil fuel prices, the share of renewable electricity, transport equipment PPPs, and the number of charging stations.

Socioeconomic factors, including the expansion of e-commerce and population density, play a pivotal role in shaping eLCV adoption patterns. High-density urban areas tend to benefit from economies of scale in logistics and infrastructure deployment, while the rise of digital commerce intensifies demand for sustainable last-mile delivery solutions. Accordingly, fostering economic activity, supporting digital trade, and advancing strategic infrastructure planning in urban centres can collectively accelerate the transition towards low-emission logistics systems. The findings of this study carry important implications for policy and business practice. The availability of charging infrastructure emerges as a key constraint, underscoring the need for targeted policy interventions to expand and optimise charging networks. Policies directed at light commercial vehicle owners and charging infrastructure providers should be strengthened to ensure adequate capacity and the strategic deployment of accessible, efficient charging solutions. New business models such as collaborative investments involving energy providers, fleet operators, and municipalities, or peer-to-peer and community-led charging networks where private and business users share infrastructure or excess renewable energy, could accelerate the development of charging infrastructure while enhancing access and cost-efficiency.

The study also calls into question the effectiveness of existing financial incentives. Despite the role of vehicle cost in adoption decisions, financial incentives currently show a

weak correlation with eLCV diffusion. This suggests that such policies may be insufficient alone and require complementary measures, such as fuel pricing strategies, infrastructure support, and more targeted policies, to have a greater impact. Policymakers should critically assess current incentive schemes and explore alternative mechanisms that address these interdependencies.

Ultimately, the findings underscore the critical importance of integrating transport and energy policy to support the transition to low-emission mobility. The positive association between eLCV adoption and the share of renewable electricity highlights the potential for synergies between renewable electricity generation and decarbonisation of the transport sector. At the same time, trends in fossil fuel prices exert a more pronounced influence on market dynamics than electricity prices, suggesting that policy measures targeting fossil fuel taxation, coupled with incentives for renewable electricity uptake, may serve as more effective levers for accelerating the adoption of eLCVs. A coherent policy framework that aligns energy and transport objectives will be essential to unlocking the full potential of low-carbon logistics.

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Declarations

Competing interest The authors declare no competing interests.

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