Sustainable Cities and Society 143 (2026) 107354

Contents lists available at ScienceDirect

Sustainable Cities and Society

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

Interpretable modelling of private electric vehicles adoption in Ireland: Bridging forecasts and policy

Afaq Khattak [*], Brian Caulfield

Centre for Transport Research, Department of Civil, Structural and Environmental Engineering, Trinity College Dublin, College Green, Dublin 2, Ireland

ARTICLE INFO

Keywords:
Private electric vehicles
Time series analysis
Deep learning
SHapley additive exPlanations

ABSTRACT

The adoption of electric vehicles (EVs) is a central pathway to reducing road transport emissions and meeting international climate goals. This study develops a two-phase hybrid forecasting and explainability framework to model private EV adoption in Ireland, while accounting for economic conditions, energy prices, policy signals, and public awareness. In the first phase, a Manta Ray Foraging Optimization–Variational Mode Decomposition–Residual Gated Recurrent Unit (MRFO VMD ResGRU) framework is employed to generate multi-horizon forecasts of monthly private EV registrations at 1-, 2-, 4-, and 6-month leads. The VMD-based signal decomposition separates trend, seasonal, and high-frequency components. Each temporal scale is then modeled through the ResGRU architecture, which results in stronger short-, medium-, and long-horizon performance than other models from the same recurrent network family. In the second phase, a surrogate-based explainable learning strategy applies SHapley Additive exPlanations (SHAP) through an Extreme Gradient Boosting (XGBoost) model that mimics the MRFO-VMD-ResGRU forecasts. The explainability analysis identifies annual average wage and the Google Trends Index (GTI), as a proxy for public interest, as the most influential factors associated with private EV adoption, followed by fuel prices. Higher income levels, stronger public interest, and higher petrol prices are positively associated with EV adoption, whereas, interestingly, higher diesel prices exhibit a negative association with uptake. This hybrid time series forecasting strategy with explainable AI gives policymakers and stakeholders transparent, data-driven insights that guide planning for private vehicle electrification and the achievement of long-term emission reduction targets in Ireland.

1. Introduction

The expansion of urban populations and their growing reliance on private vehicles have made the transport sector a leading source of air pollutants, greenhouse gases (GHG), and fossil fuel consumption (Han, 2025). According to the International Energy Agency (IEA), emissions from the transport sector have grown significantly, increasing at an average annual rate of 1.7 % from 1990 to 2022. By 2022, these emissions aggregated to nearly eight billion tonnes of carbon dioxide, representing approximately 15 % of the global total (IEA, 2023). This rise in vehicle emissions has contributed to increased concentrations of air pollutants such as $PM_{2.5}$ and ozone through distinct processes involving NO_x, volatile organic compounds, and other combustion-related emissions, thereby degrading air quality and contributing to a range of adverse health effects (Kim et al., 2025). In response, governments worldwide are prioritizing transport decarbonization, which has amplified focus on "*sustainable transportation*" as a critical pathway for reducing emissions and advancing Sustainable Development Goals (SDGs) 11 (Sustainable Cities and Communities) and 13 (Climate Action) (Arbeláez Vélez, 2024; Jnr, 2024; Küfeoğlu, 2022; Lah, 2017; Sang et al., 2026; Vaidya & Chatterji, 2019).

Within the paradigm of sustainable transportation, Electric Vehicles (EVs) are widely regarded as a key technological pathway, characterized by zero tailpipe emissions, higher energy efficiency, and reduced life cycle operational costs (Abas & Tan, 2024; Möring-Martínez et al., 2024; Sheldon & Dua, 2024). Consequently, EV adoption is largely shaped by government incentives and policy strategies that promote decarbonisation and advance progress toward the SDGs (Kim et al., 2024; Ndhlovu et al., 2025). The Global EV Outlook 2025 report by the IEA states that “*In 2024, global electric vehicle (EV) sales reached approximately 17 million units, capturing over 20 % of new car sales and marking a 25 % increase from 2023. Battery electric vehicles (BEVs) comprised over 60 % of these sales*” (IEA, 2025). This growth is largely driven by demand in China at about 11.0 million units, followed by European Union (EU)

* Corresponding author.
E-mail addresses: akhatak@tcd.ie (A. Khattak), brian.caulfield@tcd.ie (B. Caulfield).

https://doi.org/10.1016/j.scs.2026.107354
Received 10 October 2025; Received in revised form 30 March 2026; Accepted 31 March 2026
Available online 2 April 2026

with around 3.5 million units and the United States with approximately 1.5 million units in 2024.

1.1. Motivation and significance of the study

While EV adoption accelerates across the Europe, Ireland's EV registration rates continue to lag significantly behind those of its counterparts, indicating a persistent reliance on Internal Combustion Engine Vehicles (ICEVs), as shown in Fig. 1(a-b). This trend is further compounded by a strong societal dependence on private car use, even for short-distance travel. Data from the Nationwide Household Travel Survey (NHTS), conducted by the National Transport Authority (NTA) of Ireland, showed that car travel dominates short-duration trips. A large share of car journeys were under 15 min, collectively accounted for nearly half of all car trips, as illustrated in Fig. 2 (NTA, 2023). The high reliance on private ICEVs, combined with low EV adoption, implies that private cars contribute more to transport-related emissions than other modes of transport. The Environmental Protection Agency (EPA) reported that *"the transport sector in Ireland contributed roughly one-quarter of national GHG emissions, with "road transport" accounting for >90 % of this share"* (EPA, 2024). Among road transport modes, passenger cars consistently accounted for around 60 % of total GHG emissions between 2020 and 2023, as shown in Fig. 3.

To mitigate emissions from the transport sector, the Climate Action Plan (CAP) by Irish Government sets a target of "*945,000 EVs on the road and a phase-out of new ICEV sales by 2030*" (GoI, 2019). However, by December 2024, only about 360,000 EVs had been registered in Ireland, which remained well below the 2030 target (Karman et al., 2024; SIMI, 2025). This delayed transition to EVs, combined with Ireland's continued reliance on private cars, raises serious concerns about the country's long-term transportation sustainability and points to the need for a comprehensive forecasting framework to assess future EV uptake and guide policy decisions.

EV sales and registration data are common proxy measures for adoption, reflecting market uptake over time, and therefore serve as the primary input for many forecasting models. For Ireland, however, two significant challenges complicate this approach. First, the national EV registration system operates on a biannual licence plate scheme, with new identifiers issued in January and July (Revenue, 2024). This feature causes two distinct registration peaks annually, imparting a strong seasonal pattern to the time series data. Second, the underlying trend itself is also volatile. It is highly sensitive to rapid shifts in factors such as consumer preferences, public awareness, fuel prices, and government policy, all of which can cause sudden changes in EV purchase rates (Peterson, 2024). Together, these aspects produce strong seasonal patterns, recurring cycles, and multiple irregular fluctuations in the EV registration time series, resulting in a complex multi-frequency structure that makes forecasting EV uptake even more challenging. Addressing these issues is therefore critical for establishing a reliable and interpretable EV adoption forecasting framework.

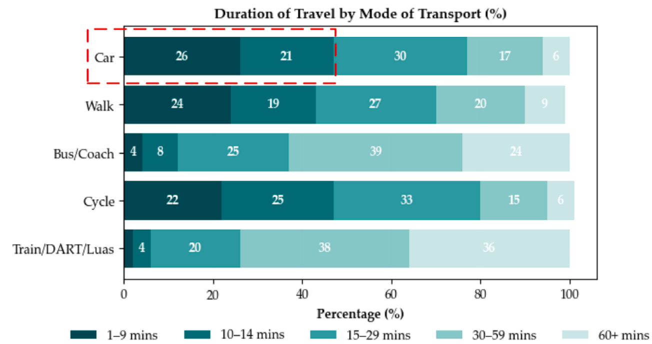


Fig. 2. Duration of travel by mode of transport in Ireland (NTA, 2023).

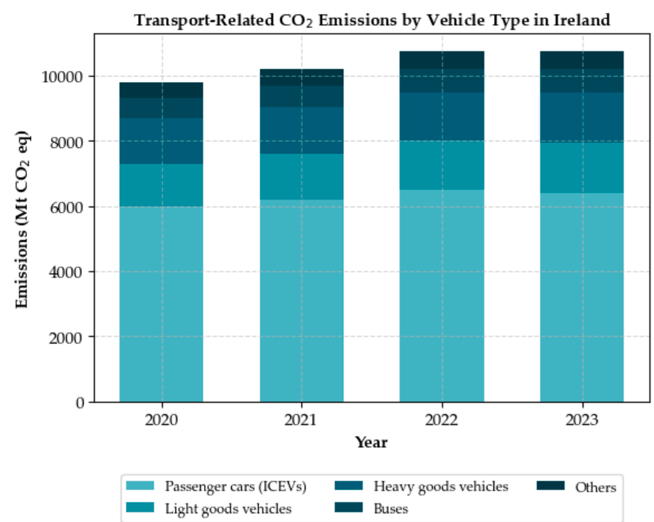
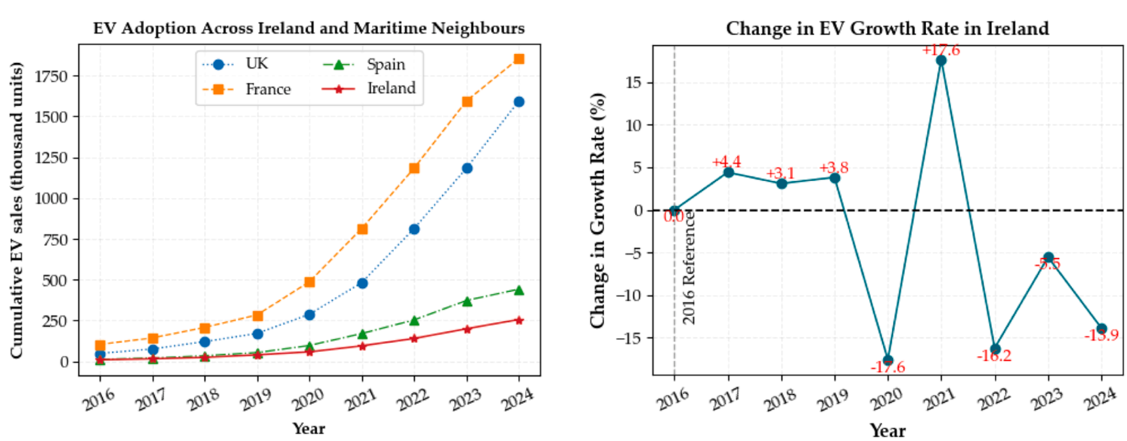


Fig. 3. Transport related CO_2 emissions in Ireland by vehicle type from 2020 to 2023.



(a) (b)

Fig. 1. EV adoption dynamics in Ireland; (a) Comparison of EV adoption in Ireland relative to its maritime neighbors; (b) Year-to-year change in the EV growth rate in Ireland relative to the 2016 baseline.

1.2. Forecasting methods of EV adoption

Forecasting EV adoption has gained critical importance for strategic, long-term planning. Reliable projections are essential for transport planners managing grid and infrastructure needs, manufacturers aligning production and supply chains, and policymakers designing effective incentives and regulations to meet national decarbonisation and sustainable transportation targets. Existing forecasting models for EV adoption can be broadly classified into four categories that include diffusion models, statistical models, artificial intelligence based models, and hybrid models. Early studies primarily adopted diffusion models such as the Gompertz, Logistic, Bass, and Generalized Bass models to simulate future EV adoption (Ayyadi & Maaroufi, 2018; Ensslen et al., 2014; Kumar et al., 2022; Santa-Eulalia et al., 2011; Zeng et al., 2013). These models remain appealing because they require relatively limited data and allow intuitive interpretation of adoption behaviour, which makes them suitable for long-term trend analysis. However, they have a number of limitations when it comes to forecasting EVs. Classical diffusion models assume smooth and monotonic adoption driven by innovation and imitation and treat adoption as a closed, homogeneous process (Han et al., 2025). As a result, these models struggle to capture abrupt market shifts, external drivers such as fuel prices and policy changes, and short-term or multi-horizon dynamics that include seasonality (Domarchi & Cherchi, 2023).

To address these limitations, statistical time series techniques such as Autoregressive Integrated Moving Average (ARIMA), Seasonal Autoregressive Integrated Moving Average (SARIMA), Exponential Smoothing (ES) have been widely used to model trends and seasonality in EV adoption (Çetin & Taşdemir, 2024; Dhankhar et al., 2024; Saraç & Ertürk, 2025; Yu et al., 2024; Zhang et al., 2017). These models have demonstrated effectiveness for short-term forecasting by capturing trends in EV adoption data. However, they face limitations when applied to time series that exhibit complex nonlinear relationships, abrupt structural changes, and high market uncertainty (Kontopoulou et al., 2023; Paliari et al., 2021). Consequently, their ability to reliably represent rapid adoption shifts and evolving policy or economic conditions remains constrained.

With the advancement of AI-based models, many researchers shifted toward the application of machine learning and deep learning strategies for EV adoption forecasting. Both standalone models and hybrid combinations of machine learning and deep learning approaches have been used to capture nonlinear relationships and complex temporal patterns in EV adoption data, such as Extreme Gradient Boosting (XGBoost) model (Miconi & Dimitri, 2023; Naseri et al., 2023; Veysi et al., 2025), Random Forest (RF) model (Shil et al., 2024), Hybrid Grey Relational Analysis – Discrete Wavelet Transform – Bidirectional Long Short-Term Memory (GRA-DWT-BiLSTM) (Liu et al., 2023), hybrid Principal Component Analysis with General Regression Neural Network (PCA-GRNN) (Wu & Chen, 2022), hybrid Long Short-Term Memory – Gradient Boosted Regression Trees (LSTM-GBRT) (Mishra et al., 2024), EVs-PredNet (Simsek et al., 2024), and hybrid ARIMA model with LSTM (Ma et al., 2023). Although these models serve as effective, high-performing alternatives to traditional statistical methods due to their ability to capture complex non-linear relationships and long-term dependencies, forecasting private EV adoption remains a significant challenge. The primary difficulty extends beyond data non-stationarity to include a complex multi-frequency structure driven by policy shifts and market responses. Addressing each frequency component individually thus becomes necessary, motivating the integration of advanced signal processing techniques with AI models.

Recent research demonstrates the efficacy of a hybrid forecasting strategy that integrates advanced signal processing techniques such as Variational Mode Decomposition (VMD), Empirical Mode Decomposition (EMD), or Complete Ensemble EMD with Adaptive Noise (CEEMDAN)—with deep learning models (Katipoğlu, 2024; Sheng et al., 2023). This hybrid approach first decomposes a complex, non-stationary time series into simpler, constituent frequency components. Then, a deep learning model is applied to capture the intricate temporal dependencies within each decomposed component. By isolating and modelling these distinct patterns separately, this strategy provide a better forecasting accuracy compared to standalone models. It has become a prominent approach for tackling complex time series forecasting challenges in domains such as energy systems (Su et al., 2025; Tang et al., 2025), air quality assessment (Gan et al., 2025; Wang et al., 2025), construction and transportation safety (Alsulami & Khattak, 2025; Khattak et al., 2025; Zhou et al., 2025), and weather forecasting (Ma et al., 2025; Oruc et al., 2025). However, to the best of our knowledge, no existing study has applied this strategy to the forecasting of EV adoption. This represents a clear research gap, as EV adoption time series exhibit strong non-linear dynamics, structural changes, and non-stationarity driven by policy interventions, market maturity, and technological diffusion. Ignoring these characteristics may lead to biased inference and unstable multi-horizon forecasting.

1.3. Drivers and constraints of EV adoption

Forecasting alone does not provide a complete understanding of EV adoption, since the assessment of the factors that contribute to uptake is equally important. However, existing studies often focus either on forecasting adoption trends or on isolated effects, without jointly capturing the dynamic interaction between these drivers and observed EV uptake. Research on EV adoption worldwide generally centers on two key dimensions. The first relates to policy and incentive mechanisms that promote uptake while the second concerns structural economic and behavioural constraints that limit adoption across different regions. Governments promote EVs as a preferred pathway to low-carbon transport through financial and non-financial incentives, such as purchase subsidies, tax relief, reduced ownership costs, and regulatory measures designed to accelerate adoption (Guo et al., 2025; Haan et al., 2025; Li et al., 2022; Zhao et al., 2024a). However, alongside these incentives, several constraints continue to limit EV adoption. For instance, even in China, which leads global EV adoption, key barriers remain related to battery performance, financial constraints, and gaps in policy implementation (Zhang et al., 2024a). In Europe, which follows China in the global EV race, adoption conditions vary substantially across countries. Italy faces persistent challenges linked to limited charging infrastructure and high vehicle costs (Giansoldati et al., 2020), while Switzerland encounters adoption constraints associated with purchase prices and driving-range limitations (Wicki et al., 2022). Across the Nordic region, despite high adoption levels, common barriers continue to include vehicle range, purchase price, and charging infrastructure availability(Noel et al., 2020). In the United States, high upfront costs and inadequate charging infrastructure remain major obstacles to wider EV uptake (Pamidimukkala et al., 2024). Similarly, India, despite its large population and growing transport demand, faces constraints related to infrastructure deficits, high vehicle prices, and limited policy incentives, which continue to slow EV diffusion (Gautam & Bolia, 2024).

Similar to other regions, Ireland's EV adoption is constrained by key barriers, which include high upfront costs, an insufficient rollout of public charging infrastructure, and the particular challenge for residents without private off-street parking (Stefaniec et al., 2025). In response, the Irish Government has introduced a range of financial and policy incentives to promote EV adoption, including purchase grants, vehicle registration tax relief, reduced motor tax, home charger support, toll reductions, and benefit-in-kind relief for company EVs. (Caulfield et al., 2022; Charly et al., 2023; Illahi et al., 2024a; Kevan, 2019; O'Brien & O'Donovan, 2024; Patil, 2023; Prakash et al., 2025; Stefaniec et al., 2025). Despite these efforts, EV uptake in Ireland remains slower than expected. This indicates that adoption is shaped not only by policy incentives but also by wider macroeconomic conditions, energy price dynamics, and labour-market factors that influence household purchasing power and vehicle ownership choices. Therefore, it is critical to assess the contribution of these factors. This need highlights a clear research gap in developing integrated frameworks that can both forecast future adoption trajectories and explain the underlying factors shaping EV uptake in Ireland. Understanding these dynamics is essential for informing effective national transport policy and advancing broader sustainable development objectives.

1.4. Study contribution and organization

This paper contributes to the EV adoption modelling and forecasting literature in three key ways.

1. First, unlike earlier studies that relied largely on linear econometric approaches such as ARMA, ARIMA, and SARIMA, or deep learning models, this study develops a novel integrated signal processing and deep learning framework to address the multi-frequency structure of EV registration time series. The Variational Mode Decomposition (VMD) is a signal processing strategy that is employed to decompose the original EV series into frequency-specific components, which allows long-term trends, seasonal patterns, and short-term fluctuations to be modeled separately (Nazarieh & Naderi Dehkordi, 2023). To improve the quality of decomposition, VMD is optimized through the Manta Ray Foraging Optimization (MRFO) algorithm, which improves mode separation and reduces information loss (Hussein et al., 2024; Wei et al., 2025). Each decomposed component, referred to as an intrinsic mode function (IMF), is then modeled independently through a Residual Gated Recurrent Unit (ResGRU) network. The residual structure improves learning stability and reduces gradient degradation, which leads to improved predictive performance under the strong non-linearity and rapid structural changes that characterize private EV adoption dynamics (Liu et al., 2025; Zhang et al., 2024b). This hybrid architecture facilitates multi-horizon forecasting and the assessment of both short-term, medium-term, and long-term private EV adoption behaviour. Prior work developed a hybrid forecasting framework for EV adoption in Ireland (Khattak & Caulfield, 2025), however it lacks a multi-horizon forecast which permits policy assessment across short, medium, and long term planning. Furthermore, it overlooks distinct frequency bands that reflect policy-driven cycles, seasonal behaviour, and short-term market variability in private EV registration data.
2. Second, the performance of the proposed MRFO–VMD–ResGRU framework is compared directly with benchmark models from the same architectural family including MRFO–VMD–ResLSTM, MRFO–VMD–GRU, and MRFO–VMD–LSTM (Jeong et al., 2021; Joshi et al., 2024; Khan et al., 2025). Maintaining identical conditions for decomposition and optimization allows us to directly attribute performance differences to the recurrent and residual design choices, thereby clarifying their role in multi-horizon EV adoption forecasting.
3. Third, while the integration of signal decomposition, deep learning, and optimization in models boosts predictive performance, it leads to an opaque "black box" framework. This opacity significantly restricts interpretability and undermines the faith required for effective policy formulation (Bodria et al., 2023; Guidotti et al., 2018; Molnar, 2020; Tripathy & Seetha, 2024). Furthermore, the inherent heterogeneity and multi-layered architecture of such hybrid frameworks actively prevent the direct application of traditional Explainable Artificial Intelligence (XAI) techniques such as SHapley Additive exPlanations (SHAP) (Lindberg & Lee, 2017; Liu et al., 2024; Makubhai et al., 2023; Swaroop et al., 2025). To address the underlying conflict between forecast and interpretability, this study proposes a surrogate-based explainable learning strategy, inspired by the recent study (Zhao & Ma, 2025). Inspired by recent methodological advances (Zhao & Ma, 2025), this study introduces a surrogate-based explainable learning strategy to reconcile the competing demands of forecasting performance and model interpretability. We employed gradient boosting models including Extreme Gradient Boosting (XGBoost) (Veysi et al., 2025), Categorical Boosting (CatBoost) (Cui, 2024), and Light Gradient Boosting Machine (LightGBM) (Hussain et al., 2025) that serve as high-fidelity, transparent proxies for the complex MRFO-VMD-ResGRU framework. This approach bridge permits reliable and meaningful utilization of SHAP-based feature attribution. As a result, our proposed strategy provides both global and local interpretations, emphasizing how economic, energy, policy, and awareness factors influence private EV adoption in Ireland.

The remainder of the paper is organized as follows. Section 2 describes the data sources and preprocessing, and the theoretical overview of proposed MRFO–VMD–ResGRU as well as surrogate based SHAP framework. Section 3 presents the forecasting results, model comparisons, and interpretability analysis. Section 4 discusses the key findings, policy implications, and study limitations.

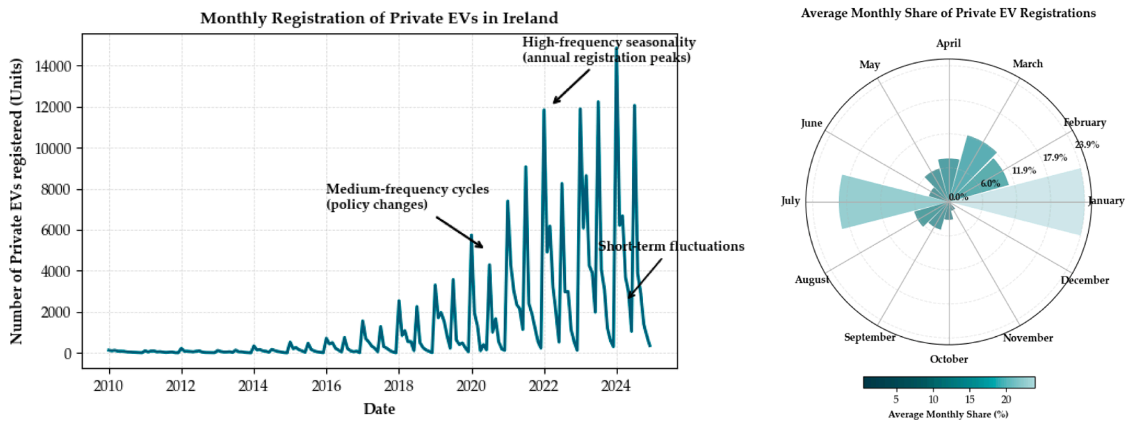
2. Data and method

2.1. Data description

This study utilizes monthly EV registration data covering the period from January 2010 to December 2024. The data were obtained from the SIMI official vehicle statistics portal (https://stats.beepbeep.ie/) (SIMI, 2025), which provides nationally aggregated and regularly updated records of vehicle registrations across Ireland. As this source represents the most comprehensive and authoritative record of vehicle uptake at the national level, the registration data are adopted in this study as a proxy for EV adoption in Ireland. Vehicle registration marks the formal entry of an EV into the national fleet, which supports its use for long-term trend analysis and forecasting. The term “EVs” covers both fully electric and hybrid-electric vehicles, comprising five engine types: Electric, Diesel Electric (Hybrid), Diesel/Plug-In Electric Hybrid, Petrol Electric (Hybrid), and Petrol/Plug-In Electric Hybrid. This classification includes both locally registered and imported new EVs.

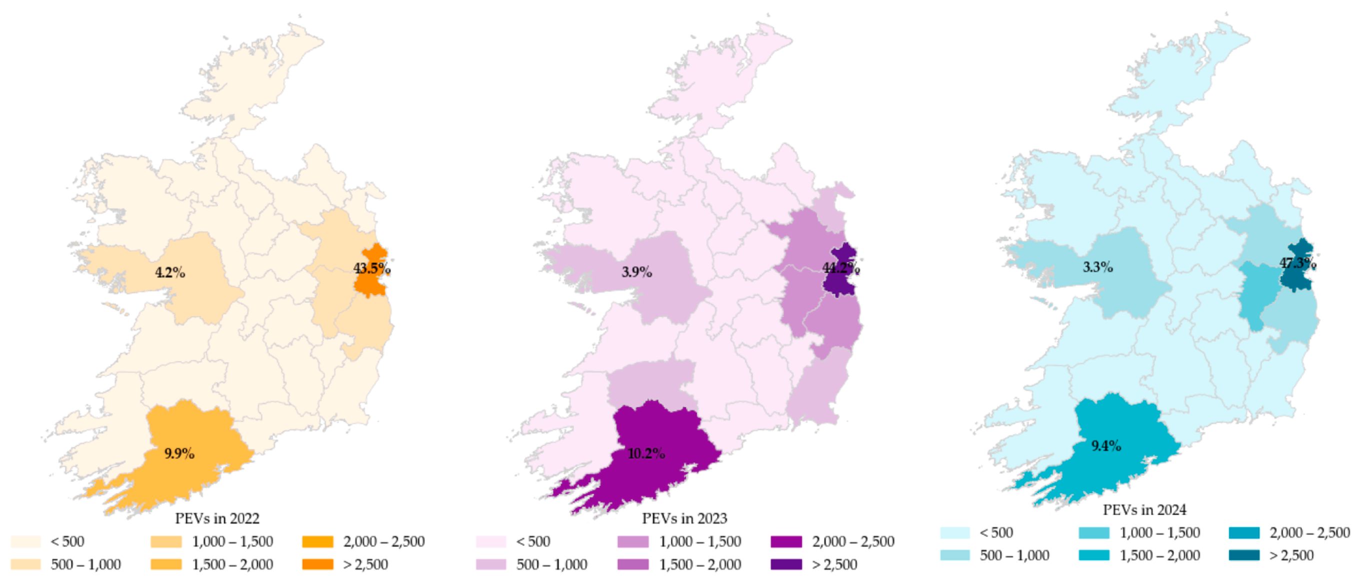
Furthermore, SIMI keeps the record of private EVs, light commercial EVs, and heavy commercial EVs. However, this study focuses exclusively on private EVs, since light and heavy commercial EVs represent only a small share of the overall EV market in Ireland. Fig. 4 depicts the nationwide monthly private EV registration pattern in Ireland. Fig. 4a shows a multiscale temporal structure. First, a long-term low-frequency component represents the EV market's steady growth over time. Second, medium-frequency components arise from recurring annual and biannual seasonal patterns that correspond to the January and July vehicle registration cycles. Third, a high-frequency component appears in the form of sharp month-to-month spikes and drops, especially in recent years, reflecting registration volatility. Fig. 4b complements the aforementioned information by presenting the average monthly share of private EV registrations, which shows a clear concentration of registrations in January and July. These months account for a disproportionately large share of annual registrations, representing high-frequency cycles that confirm the strong influence of the biannual registration system on EV purchase timing. In contrast, the remaining months exhibit lower and more evenly distributed shares, reflecting short- and medium-frequency cycles in private EV registration behaviour.

When it comes to the regional distribution of private EV adoption in Ireland, Fig. 5 presents the spatial share of private EV registrations across regions in Ireland. Data for the period 2022 to 2024 indicate that clear regional differences persist, with EV uptake concentrated in a small number of urbanized and economically stronger areas, while many regions record substantially lower adoption levels. County Dublin accounted for approximately 43–48 % of all private EV registrations,



(a) (b)

Fig. 4. Private EV registrations in Ireland from 2010 to 2024: (a) monthly private EV registration trend; (b) average monthly share of private EV registrations.



(a) (b) (c)

Fig. 5. Spatial distribution of private EV registration shares across Irish counties, showing the three counties with the highest shares in (a) 2022, (b) 2023, and (c) 2024.

followed by County Cork with 9–10 % and County Galway with 3.5–4 %. This distribution indicates that nearly half of Ireland's private EV fleet is concentrated in the Dublin region alone, which depicts the strong spatial imbalance in EV uptake across the country (Caulfield et al., 2022; CSO, 2024b).

In addition to the private EV registration time series, this study examines the dynamic impact of multiple factors on private EV uptake through a modelling framework that incorporates a set of interrelated variables with time-varying values. These factors are selected based on their direct or indirect relevance to private EV adoption in Ireland. Table 1 presents the chosen factors and their role in influencing EV uptake.

2.2. Phase-1: hybrid MRFO–VMD–ResGRU framework for multi-horizon forecast

In the first phase, the hybrid MRFO–VMD–ResGRU strategy is applied to forecast private EV registrations. This framework consists of three stages. First, the private EV registration time series is decomposed into multiple frequency bands, referred to as Intrinsic Mode Functions (IMFs). Second, each IMF is modeled through a ResGRU network. Third, the final prediction signal is reconstructed by aggregating all IMF forecasts, after which model performance is evaluated, as shown in Fig. 6.

2.2.1. Stage-1: decomposition of private EV registration time series via MRFO–VMD

As depicted in Fig. 4, the private EV registration series displays a clear multi-frequency structure, including seasonal peaks, policy-related cycles, and short-term variations. Direct modelling may obscure these dynamics, which supports decomposition into frequency-specific components before forecasting. Let $f(t)$ represent the monthly private EV registrations over time $t = 1, 2, \ldots, T$, where T denotes the length of time series. To extract informative sub-components, VMD strategy is employed. VMD decomposes the original private EV time series (signal) into K band-limited IMFs $\{u_k(t)_{k=1}^{K}\}$, by solving a constrained variational problem. The objective is to minimize the total bandwidth of all modes under the constraint that their sum equals the original signal as shown in Eq. (1).

Table 1
Factors considered in this study that influence private EV adoption in Ireland.

Category	Factor	Symbol	Relevance to EV Adoption	Ref.
Socioeconomic conditions	Consumer Price Index	CPI	It reflect inflationary pressure that affects household purchasing power and EV affordability relative to conventional vehicles.	(Somayeh Falahati Khanaman, 2025)
	GDP per Capita	GDP_{pc}	It captures overall economic prosperity at the macro level, reflecting broader market capacity for EV adoption	(Law et al., 2025; Ruoso & Ribeiro, 2022)
	Average Annual Wage	W_{avg}	It reflects household income levels that determine the ability to afford higher upfront EV purchase costs	(Halse et al., 2025; Sadeghvaziri et al., 2024)
	Unemployment Rate	$Uemp_r$	It Indicates labour market conditions that affect financial stability and consumer willingness to invest in EVs.	(Jenn et al., 2013)
Policy incentives	Private EV Purchase Grant	G_{EV}	It directly reduces the upfront cost of EVs, which lowers financial barriers and stimulates adoption	(Gerber Machado et al., 2023; Haan et al., 2025)
	Home Charger Grant	G_{HC}	It supports charging infrastructure at the household level, which reduces range anxiety and improves EV convenience.	(Knittel & Tanaka, 2025; Pellegrini et al., 2023)
Energy price dynamics	Household Electricity Price	P_{Elec}	It may determine EV affordability and influence adoption decisions	(Bushnell et al., 2022)
	Petrol Price	P_{Petrol}	Its increase can enhance the operating cost of ICEVs, which may shifts consumer preference toward EVs	(Du et al., 2024)
	Diesel Price	P_{Diesel}	It may influence the relative attractiveness of diesel vehicles compared to EVs, particularly for high-mileage users	(Hawkins et al., 2013)
Environmental targets	Transport Sector Emission Share	E^{trans}_{share}	It represent the pressure on policymakers to decarbonize transport, which often translates into stronger EV-supporting measures	(Rimpas et al., 2025; Zhao et al., 2023)
	ICEV Phase-Out Index	Φ_{ICEV}	It signals long-term policy direction, shapes consumer expectations, and guides the market transition toward EVs	(Rimpas et al., 2025)
Public awareness	Google Trends Index	GTI	It serves as a proxy for public interest and awareness of EVs, reflect real-time information-seeking behaviour	(Castellacci & Santoalha, 2025; Hao et al., 2018; Jun et al., 2018; Phillips et al., 2022)

$$\min_{\{\mu_k\},\{\omega_k\}}\left\{\sum_{k=1}^{K}\left\|\partial_t\left[\left(\delta(t)+\frac{j}{\pi t}\right)*\mu_k(t)\right]e^{-j\omega_k t}\right\|_2^2\right\} s.t. \sum_{k=1}^{K}\mu_k(t)=x(t) \tag{1}$$

where, ω_k is the center frequency of the kth mode, $\delta(t)$ is the Dirac delta function, j is the imaginary unit, and $*$ denotes convolution.

Solving Eq. (2) produces K non-overlapping IMFs with distinct temporal patterns. To avoid mode mixing or under decomposition caused by manual tuning, the Manta Ray Foraging Optimization (MRFO) algorithm (Zhao et al., 2020) is used to adaptively select VMD parameters. It is a population-based metaheuristic that balances global exploration with local exploitation through a limited number of control parameters. This structure supports stable and efficient convergence relative to other optimization strategies that include Particle Swarm Optimization (PSO), Genetic Algorithm (GA), and Grey Wolf Optimizer (GWO) (Abualigah, 2024). MRFO is governed by three mathematically defined foraging strategies including chain, cyclone, and somersault. Each strategy fulfills a distinct role in balancing exploration and exploitation (Gharehchopogh et al., 2024). For instance, *Chain foraging* updates each candidate solution by reference to the current best individual, which strengthens local search in promising regions. *Cyclone foraging* applies spiral-based position updates, which extend the search space and enhance global exploration. *Somersault foraging* periodically shifts candidate solutions around the global best position, which helps avoid local optima and maintains population diversity. Together, these strategies guide the optimization process toward the global optimum $\Theta_i = (\alpha_i, K_i)$(Abualigah et al., 2024). At each iteration, VMD is executed using the candidate parameter set, and a fitness value $\Gamma(\Theta_i)$,based on the

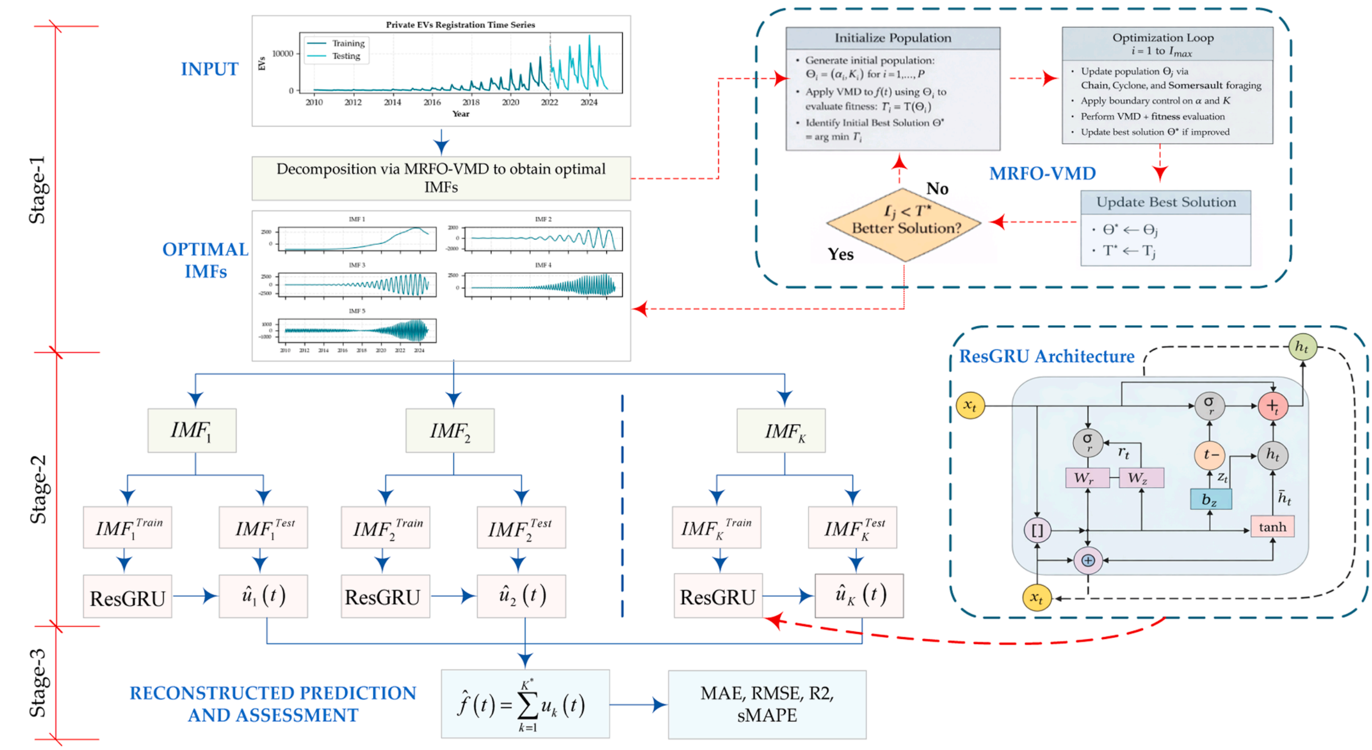


Fig. 6. MRFO-optimized VMD–ResGRU framework for private EV forecasting.

reconstructed Root Mean Square Error (RMSE), is computed. The optimal parameters Θ^*yield the final IMF set $\{u_k(t)\}_{k=1}^{K^*}$, which supports adaptive and high-quality decomposition of the Private EV registration series. Appendix Table A1 presents the pseudo-code of the MRFO–VMD procedure.

2.2.2. Stage-2: forecasting decomposed components with ResGRU optimized via MRFO

Building on Stage 1, each IMF $u_k(t)$ acts as an independent sub-series that reflects distinct oscillatory patterns, from high-frequency fluctuations to long-term trends. For forecast generations, each IMF is modeled separately using ResGRU framework, with hyperparameters tuned by MRFO. Each IMF is treated as an independent input sequence and forecast through a multi-horizon ResGRU framework. Let the input sequence of thek^{th} IMF be defined as Eq. (2).

$$\mu_k = [u_k(t-T+1), u_k(t-T+2), ..., u_k(t)] \tag{2}$$

where, T is the look-back window size.

The ResGRU network maps this input sequence to a vector of future values over a forecast horizon H, expressed as Eq. (3).

$$\hat{u}_k(t+1:t+H) = \text{ResGRU}_{\theta_k}(\mu_k) \tag{3}$$

The ResGRU architecture captures temporal dependencies within each IMF while addressing gradient degradation through residual connections. Internally, the GRU processes the input sequence step by step and maintains a hidden state. At each time step, the update gate z_t controls information retention, and the reset gate r_t regulates the influence of past states. These gates are computed as Eqs. (4) and (5), respectively.

$$z_t = \sigma(W_z u_k(t) + U_z h_{t-1} + b_z) \tag{4}$$

$$r_t = \sigma(W_r u_k(t) + U_r h_{t-1} + b_r) \tag{5}$$

It is then followed by the candidate hidden state and the updated hidden state, which are shown by Eqs. (6) and (7), respectively.

$$\widetilde{h}_t = \tanh(W_h u_k(t) + U_h(r_t \odot h_{t-1}) + b_h) \tag{6}$$

$$h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \widetilde{h}_t \tag{7}$$

After the full input sequence is processed, the final hidden state (h_T) is passed through a dense layer to generate a horizon-specific output vector, as indicated by Eq. (8), where each element corresponds to a future time step within the forecast horizon.

$$\widehat{v}_k = W_o h_T + b_o \tag{8}$$

A residual connection is then applied by adding the last observed value $u_k(t)$ to each predicted step, yielding Eq. (9).

$$\widehat{u}_k(t+1:t+H) = \widehat{v}_k + u_k(t) \tag{9}$$

This residual structure supports stable learning and preserves local temporal patterns across all forecast horizons. In order to enhance predictive performance, the MRFO strategy is applied to tune the ResGRU hyperparameters for each IMF. It is a critical step as these parameters control model capacity, learning behaviour, and convergence characteristics, which directly affect forecasting accuracy and stability (Bacanin et al., 2023). The descriptions of the ResGRU hyperparameters are provided in Table 2.

Under multi-horizon forecasting, the optimization objective for the k^{th}IMF is defined as the minimization of the average prediction error across the forecast horizon, as formulated in Eq. (10).

Table 2
ResGRU hyperparameters and their descriptions.

Hyperparameter	Description
Learning rate	Controls the step size during weight updates in training
Hidden units	Specifies the number of neurons in each GRU layer
Dropout rate	Defines the proportion of units randomly deactivated during training
GRU layers	Indicates the number of stacked GRU layers in the network

$$\underset{\theta_k}{min}\Psi_k = \frac{1}{H}\sum_{h=1}^{H}\sqrt{\frac{1}{N}\sum_{t=1}^{N}(u_k(t+h) - \widehat{u}_k(t+h))} \tag{10}$$

where, H denotes the forecast horizon, N is the number of evaluation samples, $u_k(t+h)$ is the actual value of the IMF at horizon h, $\widehat{u}_k(t+h)$ is the predicted value, $\theta_k$represents the ResGRU hyperparameter set optimized by MRFO.

2.2.3. Stage-3: reconstruction of forecasted components and performance assessment

The final prediction $\widehat{f}(t+h)$of the private EV registration series at horizon $(t+h)$ is obtained by aggregating the predicted IMF components. After each IMF $u_k(t)$ is modeled independently through the MRFO optimized ResGRU framework, the complete forecast is reconstructed by summat the IMF specific predictions at the correspond horizon. However, if an IMF shows substantially higher error, randomness, or noise similarity relative to other components, it can be excluded from the reconstruction process. A correlation screen is applied to identify acceptable IMFs. IMFs that exhibit weak or unstable association with the target series across forecast horizons are removed from the reconstruction set. Let $\widehat{u}_k(t+h)$represent the predicted values of the k^{th}IMF, obtained from MRF-optimized ResGRU described above, the final predicted time series $\widehat{f}(t+h)$at forecast step h is expressed as Eq. (11).

$$\widehat{f}(t+h) = \sum_{k=k*}\widehat{u}_k(t+h), \tag{11}$$

where, k^*represents the set of acceptable IMFs retained for reconstruction.

To evaluate the prediction performance of the individual intrinsic mode functions (IMFs) and the final reconstructed signal $\widehat{f}(t+h)$ at forecast horizon $\widehat{f}(t+h)$, Root Mean Squared Error (RMSE), normalized Root Mean Squared Error (nRMSE) and the Coefficient of Determination (R^2) are adopted as evaluation metrics. These measures are suitable for time series analysis and multi-horizon forecasting due to their complementary interpretation of accuracy and variance explanation. The RMSE quantifies the absolute magnitude of forecast errors and penalizes larger deviations more strongly, which makes it suitable for assessing overall prediction accuracy. The nRMSE measures the relative magnitude of forecast errors after scale normalization, which allows comparison across different horizons and components and the R^2 quantifies the proportion of variance in the observed series that is explained by the model, which reflects goodness of fit and stability of the forecast, as shown by Eqs. (12)–(14).

$$RMSE = \sqrt{\frac{1}{N}\sum_{t=1}^{N}[f(t+h) - \widehat{f}(t+h)]^2} \tag{12}$$

$$\text{nRMSE} = \frac{1}{\max(f) - \min(f)}\sqrt{\frac{1}{N}\sum_{t=1}^{N}[f(t+h) - \widehat{f}(t+h)]^2} \tag{13}$$

$$R^2 = 1 - \frac{\sum_{t=1}^{N}[f(t+h) - \widehat{f}(t+h)]^2}{\sum_{t=1}^{N}[f(t+h) - \bar{f}]^2} \tag{14}$$

Furthermore, to assess whether performance differences between forecasting models are statistically significant, a Wilcoxon signed-rank test (Khosravi et al., 2022; Odusami et al., 2024) is conducted with the MRFO-VMD-ResGRU model as the benchmark. This non-parametric test evaluates paired forecast errors without assumptive normality. Let y_t denote the observed series and $\widehat{y}_t^{(m)}$ the forecast from model m. The absolute error is defined as Eq. (15)

$$e_t^{(m)} = \left|y_t - \widehat{y}_t^{(m)}\right| \tag{15}$$

For a given forecast horizon, paired error differences between ResGRU and a competing model m are computed as Eq. (16).

$$d_t = e_t^{(ResGRU)} - e_t^{(m)} \tag{16}$$

The hypotheses are formulated as follow:

1. **Null hypothesis (H_0):** There is no statistically significant difference in the median prediction errors between the ResGRU model and the compared model.
2. **Alternative hypothesis (H_1):** The ResGRU model has a lower median prediction error than the compared model.

Rejection of H_0 at a significance level of $\alpha = 0.05$ indicates that MRFO-VMD-ResGRU yields statistically lower prediction errors.

2.3. Phase-2: surrogate-based explainability using SHAP

Based on the forecasting framework described in Phase 1, the proposed MRFO-VMD-ResGRU model has a black-box structure that limits direct interpretability. In order to overcome this limitation, a surrogate-based explainability strategy (Zhao & Ma, 2025) based on SHAP is implemented. SHAP allows for local interpretation at the individual forecast level, global interpretation by aggregating feature contributions across samples, and feature interaction analysis by capturing pairwise effects between explanatory variables (Virell, 2025). For this purpose, initially, the proposed forecasting MRFO–VMD–ResGRU framework $\widehat{\xi}_\rho$ is treated as a black-box function that delivers high predictive performance. Next, a set of simpler and inherently interpretable boosting model $\widehat{\xi}_{gb}$(such as, XGBoost, CatBoost, LightGBM, and AdaBoost) is trained as surrogates to mimic these predictions, thereby constructing the surrogate function. These models are widely applied in transport research and support SHAP-based feature attribution (Dong et al., 2022; Hao et al., 2024; Li et al., 2024a; Parsa et al., 2020; Sun et al., 2024). The final surrogate is selected after achieving a *high level of fidelity* between $\widehat{\xi}_\rho$and $\widehat{\xi}_{gb}$ (predictions from the surrogate closely match those of the MRFO-VMD-ResGRU model) and *high Faithfulness* (SHAP values from the surrogate reliably capture the influence of each feature and are validated through feature injection tests) (Rudin, 2019).

Let $\widehat{y}_{i,t}$ be the MRFO-VMD-ResGRU forecast for instance i at time step t. Let $\mu_i$and σ_i denote the historical mean and standard deviation of the target variable for instance i, respectively. The forecast is standardized using the z-score transformation as Eq. (17). Furthermore, let $x_{\text{eng},t}$ denote the engineered feature vector at time t. The surrogate boosting model is then trained to approximate the standardized forecast output as Eq. (18).

$$z_{i,t} = \frac{\widehat{y}_{i,t} - \mu_i}{\sigma_i} \tag{17}$$

$$\widehat{\xi}_{gb}\left(x_{\text{eng},t}\right) \approx z_{i,t} \tag{18}$$

This formulation allows SHAP values from the surrogate model to interpret forecasts produced by the proposed MRFO-VMD-ResGRU framework. After training the surrogate, SHAP values are computed to attribute each feature effect on the forecast. The surrogate prediction is decomposed into based value (ϕ_0) and additive feature contributions (ϕ_j), as expressed in Eq. (19) (Li et al., 2024b; Timilsina et al., 2024). These contributions are first obtained in normalized space, then rescaled to the original forecast scale in Eq. (20).

$$\widehat{\xi}_{gb}(x) \approx \phi_0 + \sum_{j=1}^{p}\phi_j \tag{19}$$

$$\phi_{j,\text{denorm}} = \phi_j(\sigma_i) \tag{20}$$

If required, a calibration factor(π) (Eq. (21)) is applied to align the total SHAP attribution with the original model forecast, which yields adjusted SHAP values in Eq. (22).

$$\pi = \frac{\widehat{y}_{i,t}}{\sum_{j=1}^{p} \phi_{j,\mathrm{denorm}}} \tag{21}$$

$$\phi_{j,\mathrm{calib}} = \pi(\phi_{j,\mathrm{denorm}}) \tag{22}$$

where, p is the number of features.

The calibration in Eq. (22) enforces additivity between the adjusted SHAP values and original forecast, which preserve coherence between explanation and prediction, as shown in Eq. (23)

$$\phi_0 + \sum_{j=1}^{p} \phi_{j,\mathrm{calib}} = \widehat{y}_{i,t} \tag{23}$$

3. Results and discussion

This section presents the empirical findings of the study and is structured around the two-phase framework discussed earlier: (1) multi-horizon forecasting of private EV adoption and (2) interpretation of adoption drivers through XAI-based learning. In the first phase, the forecasting analysis relies exclusively on monthly private EV registration data in Ireland, which are employed as a proxy for adoption. The data are obtained from SIMI and cover the period from January 2010 to December 2024, including both newly registered and second-hand private EVs. The registration series captures observed market uptake over time and serves as the sole input to the proposed MRFO–VMD–ResGRU forecasting framework. The dataset spans January 2010 to December 2024 and is divided into training–validation (80 %, January 2010 to December 2021) and testing (20 %, January 2022 to December 2024) subsets, as illustrated in Fig. 7. This partition supports model calibration on the majority of observations and subsequent evaluation on out-of-sample data (Tuli et al., 2022).

In the second phase, the interpretability analysis examines the role of economic, policy, energy, and awareness-related factors that shape private EV adoption dynamics. For this purpose, a set of explanatory variables is compiled from multiple official and publicly available sources, with all series aligned to a monthly frequency over the same 2010–2024 period. To achieve data standardization, selected explanatory factors were preprocessed before further analysis. For instance, the Irish government introduced an G_{EV} of €5000 on 1 January 2011, which was reduced to €3500 on 1 January 2023 (Stefaniec et al., 2025). For analysis, a value of 1 represents the €5000 period, while 0.7 represents the €3500 period, reflecting the proportional grant level. All other periods are assigned a value of 0. Similarly, was introduced by Irish government on 1 January 2018 at €600, assigned a value of 1, reduced to €300 on 1 January 2024, assigned a value of 0.5, and set to 0 in all other periods. Similarly, the $G_{HC}$was introduced by the Irish Government on 1 January 2018 at a value of €600, which is assigned a normalized value of 1. The grant was reduced to €300 on 1 January 2024, corresponding to a normalized value of 0.5, while all other periods are assigned a value of 0. Furthermore, online search activity serves as an early indicator of purchase intention and initial adoption for the technology-intensive products such as private EVs (Du & Hsieh, 2023). Accordingly, this study uses *GTI* relative search volume as a proxy for public interest or awareness, consistent with its application in health, tourism, marketing, and technology adoption research (Maugeri et al., 2023; Mohamad & Kok, 2019; Ramadan et al., 2024; Vasconcellos-Silva et al., 2017). For analysis, *GTI*data for five EV-related search terms were aggregated into a normalized index, as shown in Eq. (24).

$$GTI_t = 100 \times \frac{ASV_t}{\max(ASV_t)} \tag{24}$$

Moreover, as discussed earlier, the CAP19 sets 2030 as the target year for the phase-out of new ICEV sales. Since 2019, the remaining transition period toward 2030 follows a defined countdown. This countdown is converted into a normalized indicator Φ^t_{ICEV}, as defined in Eq. (25).

$$\Phi^t_{ICEV} = \frac{Month^t - July2019}{Dec2030 - July2019} \tag{25}$$

Where, $Month^t$ refers to the calendar month of observation expressed.

By December 2024, the index reached a value of 0.47, which indicates that nearly half of the transition period had elapsed. As the target year approaches, this timeline may contribute to a growing sense of urgency and expectation among consumers regarding future vehicle choices. Table 3 presents the descriptive statistics and data sources, while Appendix A provides the complete temporal profiles of these parameters, illustrated in Figures 1A–5A.

3.1. Private EV series decomposition and multi-horizon forecast results

In this stage, the proposed MRFO–VMD strategy addresses the complex dynamics of the private EV registration series by decomposing it into optimal, distinct frequency modes known as IMFs. Through a parameter search where the IMFs (K) varied from 3 to 10, the penalty term(α) from 500 to 1500, and the noise tolerance (π)from 1×10^{-6} to 1×10^{-3}., the MRFO algorithm optimized the VMD process. This decomposition not only manages non-stationarity driven by trend and seasonality but also disentangles the inherent multi-frequency structure and non-linear interactions caused by policy shifts and market responses. Using MRFO, the optimal VMD parameters were determined to

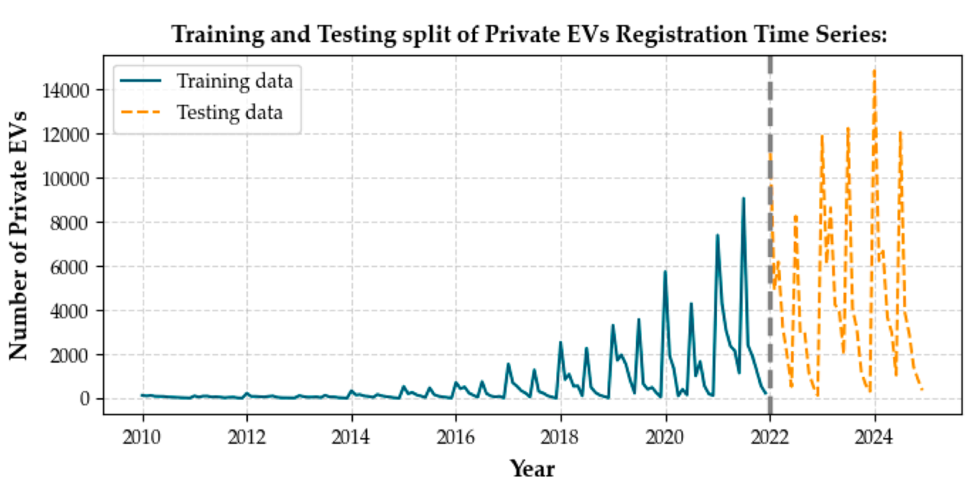


Fig. 7. Training and testing split of the private EV registration time series.

Table 3
Descriptive statistics of factors influencing private EV adoption in Ireland and corresponding data sources.

Parameters	Descriptive Statistics				Source
	Mean	Std Dev	Max	Min	
CPI	109.82	7.94	130	100	https://www.cso.ie/en/releasesandpublications/ep/p-cpi/consumerpriceindexjanuary2025
GDP_{pc} (in 10,000)	7.54	2.13	10.73	4.87	https://fred.stlouisfed.org/series/NYGDPPCAPKDIRL
W_{avg} (in 1000)	39.09	3.49	46.00	35.00	https://www.cso.ie/en/releasesandpublications/
$Uemp_r$	8.81	4.21	16.10	4.10	https://www.cso.ie/en/statistics/labourmarket/monthlyunemployment/
G_{EV}	0.89	0.26	1.00	0.00	https://www.seai.ie/grants/electric-vehicle-grants
G_{HC}	0.43	0.48	1.00	0.00	https://www.seai.ie/grants/electric-vehicle-grants/electric-vehicle-charging/electric-vehicle-home-charger-grant
P_{Elec}	24.17	4.86	37.48	17.05	https://www.seai.ie/
P_{Petrol}	149.71	18.24	213.20	121.10	https://www.theaa.ie/aa-membership/fuel-prices/
P_{Diesel}	142.32	21.65	205.00	105.40	https://www.theaa.ie/aa-membership/fuel-prices/
E^{trans}_{share}	19.49	0.83	21.40	18.10	https://www.seai.ie/data-and-insights/seai-statistics/transport
Φ_{ICEV}	0.09	0.15	0.52	0.00	https://www.simi.ie/en/environment/drive-greener/transition-to-zero-emissions
GTI	29.48	28.65	100.00	1.04	https://trends.google.com/

Furthermore, to assess non-linearity and non-stationarity in the private EV registration series, an initial exploratory analysis was conducted. The Autocorrelation (ACF) and Partial Autocorrelation (PACF) plots reveal significant dependence at multiple and seasonal lags, indicating pronounced temporal persistence and seasonality. The Augmented Dickey–Fuller test statistic of 1.04 (p = = 0.995) further confirms non-stationarity, which appears to be driven by both trend and seasonal components, as shown in Fig. 8.

be K = = 5, α = 1000, and τ = 1 × 10⁻⁶. This configuration produced a set of IMFs that distinctly capture the key temporal characteristics of the private EV registration series, as illustrated in Fig. 9. These components reflected a long-term trend (IMF1), low-frequency variations with greater amplitude after 2018 (IMF2), medium-frequency seasonal cycles with increased regularity after 2020 (IMF3), high-frequency effects associated with Ireland's biannual vehicle registration system (IMF4), and short-term irregular fluctuations (IMF5).

3.2. Multi-horizon forecasting via MRFO-VMD-ResGRU

Based on MRFO–VMD, five optimal IMFs are obtained, each modeled using a dedicated ResGRU with hyperparameters tuned via MRFO. The convergence behavior of MRFO for all five IMFs across forecast horizons is presented in Appendix A (Fig. 6A), while the optimized hyperparameter configurations are reported in Appendix A (Table A2). In parallel, horizon-wise Pearson correlation screening shows that IMF1 declines sharply (0.880 to 0.220; mean 0.591), whereas IMF2–IMF5 remain stable (means 0.935–0.983), leading to the exclusion of IMF1 and retention of IMFs 2–5 for reconstruction (Appendix A Table A3) (Wang et al., 2024; Xia et al., 2025).

Furthermore, the IMF-level plots demonstrate a clear distinction between IMF1 and others IMFs (Fig. 10). Across all forecast horizons, IMF1 shows substantial divergence between actual and predicted values, with errors in both amplitude and trend that worsen at longer horizons, indicating poor forecasting ability. In contrast, IMFs 2–5 exhibit strong alignment with the actual signals, with near-perfect overlap at short horizons and only minor deviations in amplitude and phase at longer horizons, while preserving the overall oscillatory structure.

Fig. 11 depicts a structured pattern of horizon-wise performance across IMFs 2–5. At 1-month horizon, all IMFs demonstrate low nRMSE and a high R^2, with IMF 4 and 5 presenting the smallest errors and highest goodness of fit. As the horizon extends to 2 months, nRMSE rises and R^2 reduces slightly. However, IMF 4 and IMF 5 retain strong predictive quality compared to IMF 2 and IMF 3. Over a 4-month period, IMF 2 and IMF 3 displays greater degree of error growth, while IMF 4 and IMF 5 maintain low nRMSE and R^2 values above 0.90. At a 6-month horizon, this sequence remains unaffected, with IMF 4 and IMF 5 displaying the most stability and IMF 2 remaining the weakest. While forecast uncertainty increases with horizon length, IMF 4 and IMF 5 continue to have low error and high R^2.

The final reconstructed series and horizon-wise metrics in Fig. 12(a-b) demonstrate that forecast quality slightly degrades in a smooth and structured manner as lead time increases. At a 1-month time horizon, the reconstructed signal closely tracks the actual series, with well-aligned peaks and troughs and only minor amplitude deviations, as demonstrated by the low nRMSE and high R^2. At the 2-month horizon, minor phase shifts and moderate amplitude errors appear, but the broader temporal pattern remains intact. Divergence becomes slightly more visible over a 4-month period, due to growing under- and overshoots around turning points, which leads to an apparent rise in nRMSE and a

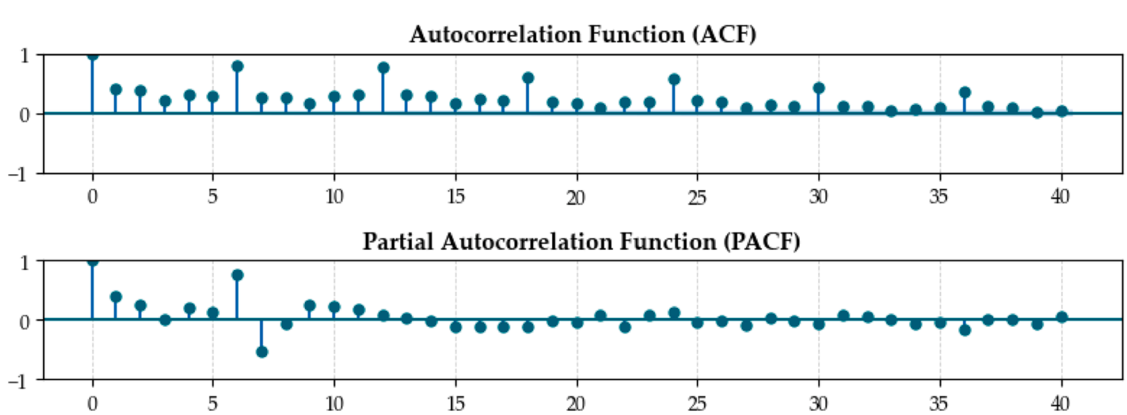


Fig. 8. ACF and PACF plots of private EV registration time series.

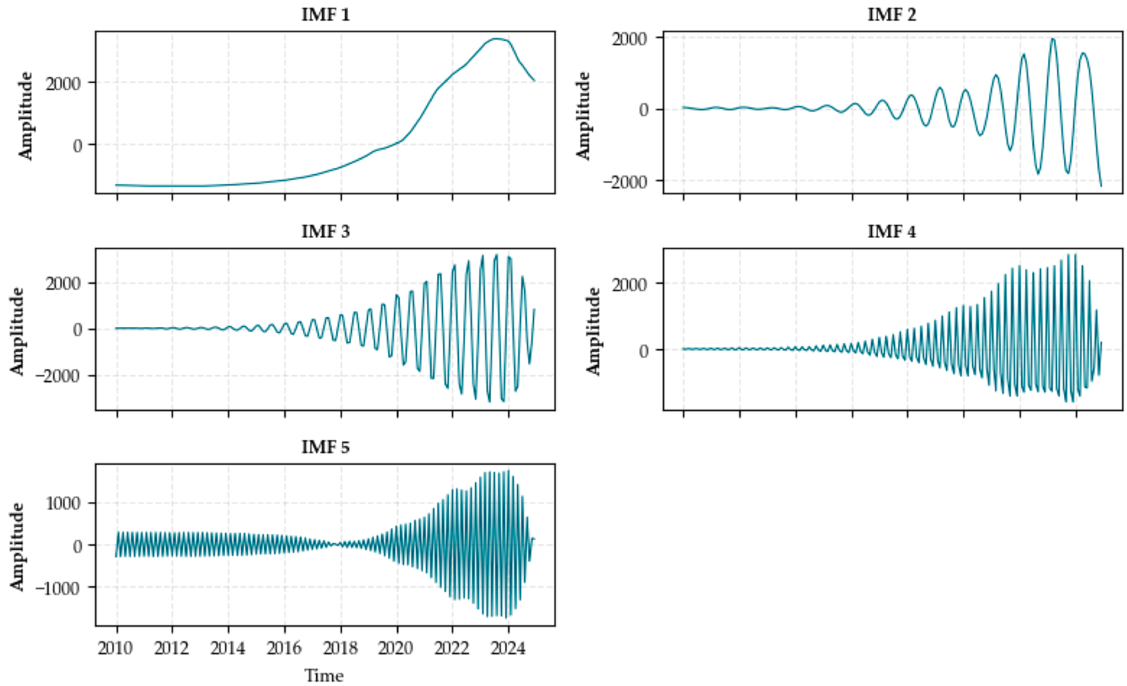


Fig. 9. Decomposition of private EV registration time series using MRFO-VMD.

drop in R^2. The reconstruction still captures the dominant oscillatory structure at the 6-month horizon, but there exists greater phase drift and amplitude mismatch, results in a lower R^2 and the largest nRMSE.

3.3. Comparison of MRFO-VMD-ResGRU against alternative models

3.3.1. Performance comparison

Across the four forecast horizons, MRFO-VMD-ResGRU follows the actual EV registration profile with closer alignment than MRFO-VMD-GRU, MRFO-VMD-LSTM, and MRFO-VMD-ResLSTM, with gains that grow as the lead time extends from 1 to 6 months, as shown in Fig. 13 (a–d). The plots show that seasonal peaks near the start of each year and the mid-year troughs stay well aligned under MRFO-VMD-ResGRU, while the GRU, LSTM, and ResLSTM variants exhibit phase drift and amplitude inflation that intensify at the 4- and 6-month horizons. These departures appear as peaks that arrive too early or too late and crests that rise beyond observed levels, which increases divergence from the true private EV registration path as the horizon expands. By contrast, MRFO-VMD-ResGRU preserves both the temporal position and the scale of cyclical movements, which keeps the forecast trajectory closer to the observed pattern even under longer lead times.

Moreover, the radar plots for nRMSE and R^2 over 1-, 2-, 4-, and 6-month horizons provide a consistent perspective on relative model competence, as demonstrated in Fig. 14(a-b). In terms of nRMSE, MRFO-VMD-ResGRU has the smallest radial span at each horizon, which indicates the lowest normalized error when compared to MRFO-VMD-GRU, MRFO-VMD-LSTM, and MRFO-VMD-ResLSTM (Fig. 14a). The discrepancy becomes more obvious at the 4- and 6-month steps, when GRU and LSTM demonstrate significant error growth and ResLSTM demonstrate only partial containment, whereas MRFO-VMD-ResGRU maintains a slower rate of error increase, which indicates better control of both peak magnitude and trough depth.

Similarly, the R^2 radar plots show the same order. Compared to the other variants, MRFO-VMD-ResGRU displays the highest values over all horizons, which implies that it accounts for a greater percentage of the variability in observed private EV registrations (Fig. 14b). The R^2 of GRU and LSTM drastically decreases as the horizon grows longer, demonstrating a loss of structural alignment with the true series. ResLSTM also deteriorates after short lead times. MRFO-VMD-ResGRU, on the other hand, preserves a greater percentage of explained variance even after six months, revealing that its forecasts maintain seasonal coherence and trend under long lead times.

3.3.2. Statistical significance test

Table 4 presents the Wilcoxon signed-rank test that compares MRFO-VMD-ResGRU with MRFO-VMD-GRU, MRFO-VMD-LSTM, and MRFO-VMD-ResLSTM across four forecast horizons from T + 1 to T + 6. At T + 1, MRFO-VMD-ResGRU does not show a statistically significant difference relative to MRFO-VMD-GRU with a *p*-value of 0.067, which indicates comparable short-horizon accuracy, while statistically significant differences appear against MRFO-VMD-LSTM and MRFO-VMD-ResLSTM with *p*-values below 0.05. From T + 2 onward, all pairwise tests yield *p*-values below 0.05, which supports rejection of the null hypothesis and confirms that MRFO-VMD-ResGRU has lower median prediction errors than MRFO-VMD-GRU, MRFO-VMD-LSTM, and MRFO-VMD-ResLSTM. The lower Wilcoxon statistics at longer horizons such as T + 4 and T + 6 further indicate stronger separation between MRFO-VMD-ResGRU and the other models, which shows that its predictive advantage becomes more pronounced as the forecast horizon extends.

3.4. Explainability results through SHAP-based analysis

3.4.1. Surrogate model selection and validation

Beyond forecast accuracy, this study also examines how dynamic external factors, as discussed in Section 2.3, shape adoption patterns over time, which extends the analysis toward a policy-relevant understanding of EV adoption dynamics. Although our proposed MRFO–VMD–ResGRU model achieved the highest predictive accuracy among all benchmarks, deep learning models with temporal and exogenous inputs remain opaque (ŞAHiN et al., 2025). This opacity limits direct interpretability and motivates the use of SHAP interpretation technique. Since direct SHAP analysis on the MRFO–VMD–ResGRU model is not feasible, a surrogate modelling strategy was therefore adopted (Hassija et al., 2024). To identify the most suitable surrogate for the MRFO–VMD–ResGRU model, this study trained four

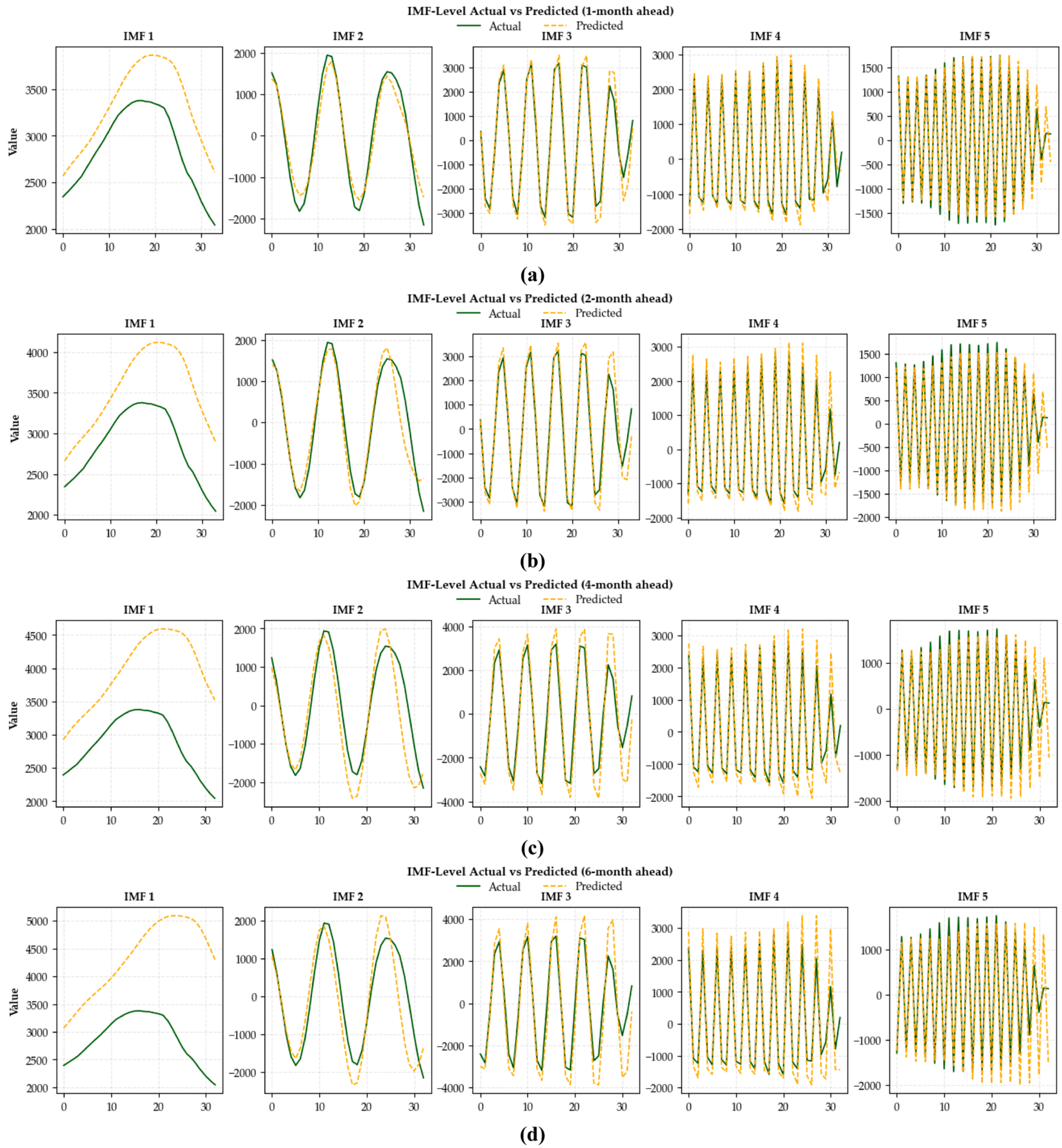


Fig. 10. IMF-level actual versus MRFO-VMD-ResGRU predicted signals across multiple forecast horizons; (1) 1-month ahead; (2) 2-month ahead; (3) 4-month ahead; (d) 6-month ahead.

gradient-boosted models, namely XGBoost, CatBoost, LightGBM, and AdaBoost, as simpler and more interpretable surrogates. Two validation stages were applied to assess forecast replication accuracy and feature attribution reliability, as illustrated in Fig. 15. Among the candidate models, XGBoost reproduced the hybrid forecasts with near-perfect alignment ($R^2 = 1.00$), followed by CatBoost ($R^2 = 0.993$), while LightGBM ($R^2 = 0.642$) and AdaBoost ($R^2 = 0.757$) showed weaker correspondence, as shown in Fig. 15a. Feature attribution reliability based on feature injection tests further confirmed that SHAP attributions from the XGBoost surrogate closely matched predefined causal effects, as shown in Fig. 15b These findings signify the implementation of XGBoost as a reliable interpretability proxy for assessing the key drivers of private EV adoption dynamics in Ireland.

3.3.2. SHAP global interpretation

Using XGBoost as a surrogate for the MRFO–VMD–ResGRU framework, SHAP analysis was applied to reveal the global contribution of input features to private EV (PEV) forecasts. This analysis provides an

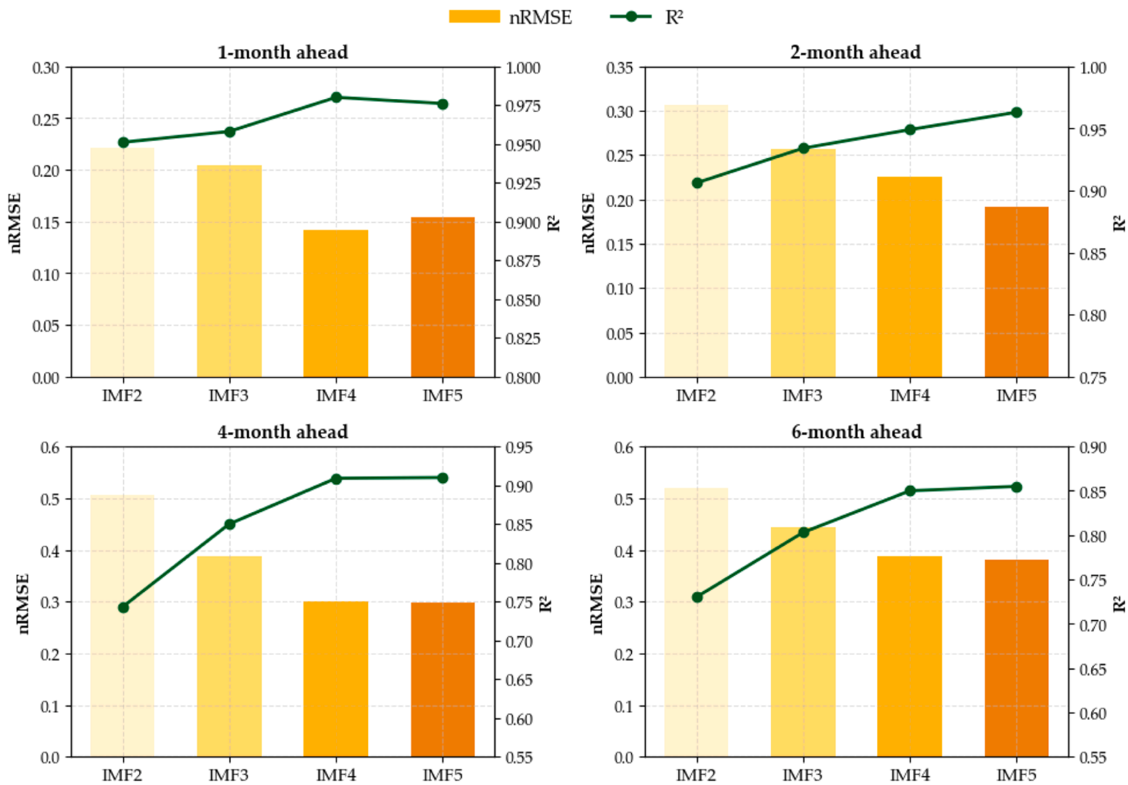


Fig. 11. Performance measures of each IMF including nRMSE and R^2 for 1-month ahead, 2-month ahead, 4-month ahead and 6-month ahead forecast.

aggregated view of feature importance across the entire prediction horizon, which clarifies how each dynamic factor influences model outputs and shapes overall adoption patterns. Fig. 16 shows the global interpretation results of the model. Fig. 16a presents the global feature importance plot, which ranks variables by their overall contribution to the model forecast. Fig. 16b shows the SHAP summary plot, where each point corresponds to one observation for a given feature. The horizontal axis represents the direction and magnitude of feature impact on the model output. Red points indicate higher feature values, purple indicate medium feature value, while blue points indicate lower feature values. Points on the right reflect a positive contribution to the forecast, whereas points on the left reflect a negative contribution.

Based on the analysis, the most influential contributor to EV adoption is W_{avg}, which has the highest mean SHAP value (+1092.9) as shown in the feature importance plot. In the SHAP summary plot, red points corresponding to W_{avg} appear predominantly on the right side, which indicates that higher W_{avg} levels exert a positive influence on private EV adoption. Households with higher wages are therefore more capable of meeting this financial requirement, even after purchase grants, which explains the strong positive contribution of income to private EV adoption. This finding aligns with earlier studies, which show that affordability is the main constraint for mass-market private EV adoption. EV uptake is concentrated among higher-income households, while lower-income households respond mainly when substantial subsidies reduce the upfront purchase cost (Muehlegger & Rapson, 2018; Turrentine et al., 2018). In Ireland, for instance, entry-level private EVs in 2024 were priced between approximately €31,995 and €46,900, while the W_{avg} was around €46,000 (CarsForSaleDonegal.ie, 2025; MG Motor Ireland, 2025). This means that purchasing an entry-level private EV can correspond to nearly a full year of gross income for an average earner. As a result, affordability plays a decisive role, and private EV adoption becomes more likely among households with higher income levels, where upfront cost constraints are less binding. Evidence from private EV ownership analysis in USA based on National Household Travel Survey (NHTS) 2022 data also showed that households with higher income and multiple vehicles are more likely to own private EVs (Sadeghvaziri et al., 2024).

The next most influential feature is the GTI, with a mean SHAP value of +680.04. In the SHAP summary plot, red points appear mostly on the right side, which indicates that higher GTI values have a positive impact on private EV uptake. This effect reflects public attention toward private EVs and aligns with earlier studies that link online search activity to consumer awareness and technology adoption. Online search interest acts as a meaningful signal for demand, as it mirrors how potential buyers explore information and evaluate emerging vehicle technologies. Prior research also reported that higher Google search interest shows a strong association with greater private EV consideration and sales, since search intensity captures information search, awareness formation, and purchase intent related to private EVs (Castellacci & Santoalha, 2025; Green Car Stocks, 2022; McElgunn, 2018).

Furthermore, P_{Diesel} and P_{Petrol} rank third and fourth in their influence on private EV uptake, with mean SHAP values of +407.57 and +337.67, respectively. However, it has been observed from the SHAP summary plot for more blue and purple points are clustered on the right side and more red points on the left side. This pattern indicates that lower to medium diesel prices contribute positively to private EV uptake, while higher diesel prices exert a negative contribution. This pattern is more likely due to the fact that even at higher diesel prices, the effect remains negative for private EV uptake. In Ireland, diesel ICEV users often rely on their vehicles for long-distance and high-mileage travel, and limited EV charging infrastructure intensifies range anxiety, which discourages a switch to EVs despite higher diesel prices. This aligns with the SEAI report on private EV uptake, which demonstrates that range anxiety is closely linked to public charging access and that gaps in infrastructure and awareness reduce consumer willingness to invest in private EVs (SEAI, 2020). Prior studies also indicate that range anxiety and limited charging access remain major barriers to private EV adoption, which places higher risk on diesel vehicle users who depend on long-distance and high-mileage travel (Micheal, 2024; Wood, 2022).

In the case of P_{Petrol}, a larger share of red points appears on the right

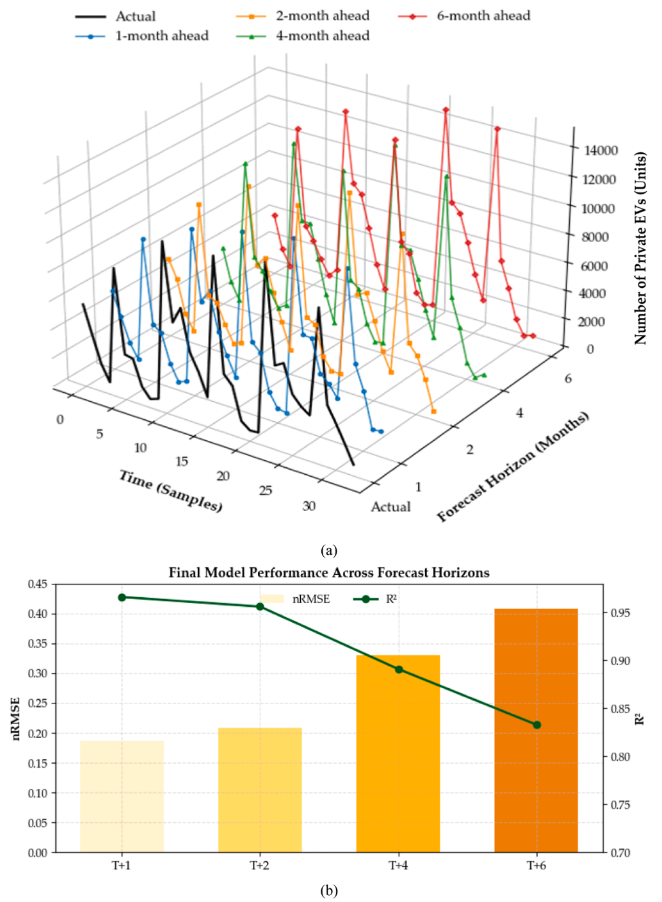


Fig. 12. Final reconstructed of MRFO-VMD-ResGRU predicted series (a) 3-dimensional plot between the actual time series and the MRFO–VMD–ResGRU multi-horizon forecasts; (b) Performance across forecast horizons.

side, which reflects a positive impact on private EV uptake. This pattern aligns with prior empirical research that reports a much stronger response of private EV demand to gasoline prices. A study reported that gasoline prices exert roughly four to six times the effect on private EV adoption (Bushnell et al., 2022). Similarly, a study also revealed that BEV sales respond more strongly to gasoline price increases than hybrid alternatives (Fei et al., 2025; Wang et al., 2022). Other features such as CPI, P_{Elec}, and $Uemp_r$have moderate effects. Interestingly, both Irish government grants (G_{EV} and G_{HC}) showed negligible influence, which is likely due to recent reductions or restricted eligibility. A recent study on EV adoption in Ireland reported that a reduction in the private EV purchase grant from €5000 to €3500 lowered vehicle affordability and increased the likelihood that households require additional borrowing to complete a purchase (Stefaniec et al., 2025).

3.3.3. SHAP-based interaction analysis

SHAP-based interaction analysis extends standard SHAP global interpretation by quantifying how pairs of input features jointly influence the model output, as shown in Fig. 17. The SHAP dependency plot for W_{avg} and P_{Petrol} shows how the income effect on private EV adoption varies across petrol price levels (Fig. 17a). At lower wage levels, SHAP values remain negative irrespective of petrol price. When average annual wage reaches around €38,000, SHAP values shift toward positive even under low to medium petrol prices. As wage increases further, higher petrol prices correspond to larger SHAP values, which shows that their combined effect intensifies, shown by clustering of green-colored points at the upper end and exerts a strong positive impact on private EV adoption. This interaction aligns with previous study, which highlighted that households with higher incomes are more responsive to P_{Petrol}increases when considering a shift to private EVs and reflects both affordability and greater sensitivity to operating cost savings (Zhao et al., 2025).

The SHAP dependence plot for P_{Petrol} (Fig. 17b) shows that P_{Petrol}above 170 cent per litre are generally linked to a higher likelihood of private EV adoption especially when GTI values are high. At lower P_{Petrol} (120–160 cent per litre), SHAP values remain close to zero or slightly negative, regardless of GTI, which indicates limited effect on adoption. Once P_{Petrol} rises beyond 170 cent per litre, SHAP values shift upward, with the effect more evident when GTI is above 50, as shown by the clustering of blue-colored points. This interaction pattern indicates that the influence of fuel price on adoption becomes stronger when public attention to private EVs is high and reflects a combined effect of economic cost pressure and consumer awareness.

In the SHAP dependency plot for diesel price P_{Diesel} shown in Fig. 17c, values remain mostly positive or close to zero when prices are between about 120 and 160 cent per litre. Once the price moves beyond roughly 170 cent per litre, SHAP values fall steeply, with some reaching nearly –4000. even with higher value of *GTI*. This decline indicates that higher P_{Diesel} remain acceptable for consumers in Ireland, which may reflect the reliance of long-distance diesel users who face operational constraints and limited charging facilities in rural areas (Charly et al., 2023; Illahi et al., 2024b).

3.3.4. SHAP local interpretations

To complement the global feature ranking, SHAP waterfall plots show how individual factors contribute to specific private EV adoption outcomes by decomposing each prediction into positive and negative feature effects relative to a baseline (Alam et al., 2025). Each plot starts from the model baseline, which represents the average adoption level, and then shows how individual feature effects modify this value to produce the final case-specific forecast. Three representative points within the analysed period from January 2010 to December 2024 are examined. 1) the early private EV adoption stage; 2) the post-COVID-19 recovery period, and; 3) the recent private EV mature market phase, as shown in Fig. 18. This approach illustrates how economic conditions, policy measures, and public awareness shape private EV adoption across different stages of market development. Other cases from the dataset can be assessed in a similar way.

(a) Case 1: Early Premature Phase of Private EV Adoption in Ireland (2012)

During the early phase of private EV adoption in Ireland from 2010 to 2012, when the market was undeveloped and public awareness, financial grants, and charging infrastructure were limited, a randomly selected instance from the dataset representing this stage corresponds to February 2012 (Fig. 18a). For this instance, it has been observed that W_{avg} below €35,600 exert the largest negative effect (–944.74), which indicates a restricted purchasing power for acquiring private EVs. In addition, the low GTI value of 7.25 contributes negatively (−546.53), indicating low levels of public interest in EV-related information at that time. This subdued online search activity points to limited awareness and information demand, which constrained consumer readiness and hindered private EV adoption in the early stage. Early research during that period already emphasized the value of internet browsing and online search data as a useful indicator of consumer behaviour and vehicle sales trends (Carrière-Swallow & Labbé, 2013; Chamberlin, 2010).

On other hand during early phase, P_{Diesel} of 154.4 contribute positively (+409.49) and showed that at some extend, P_{Diesel} encouraged interest in private EV alternatives. Furthermore, a low CPI of 104.8 in Ireland during that time adds a positive contribution (+241.07), which potentially indicates lower inflation and greater household spending capacity. Nonetheless, the strong negative impacts from $W_{avg}$and GTI

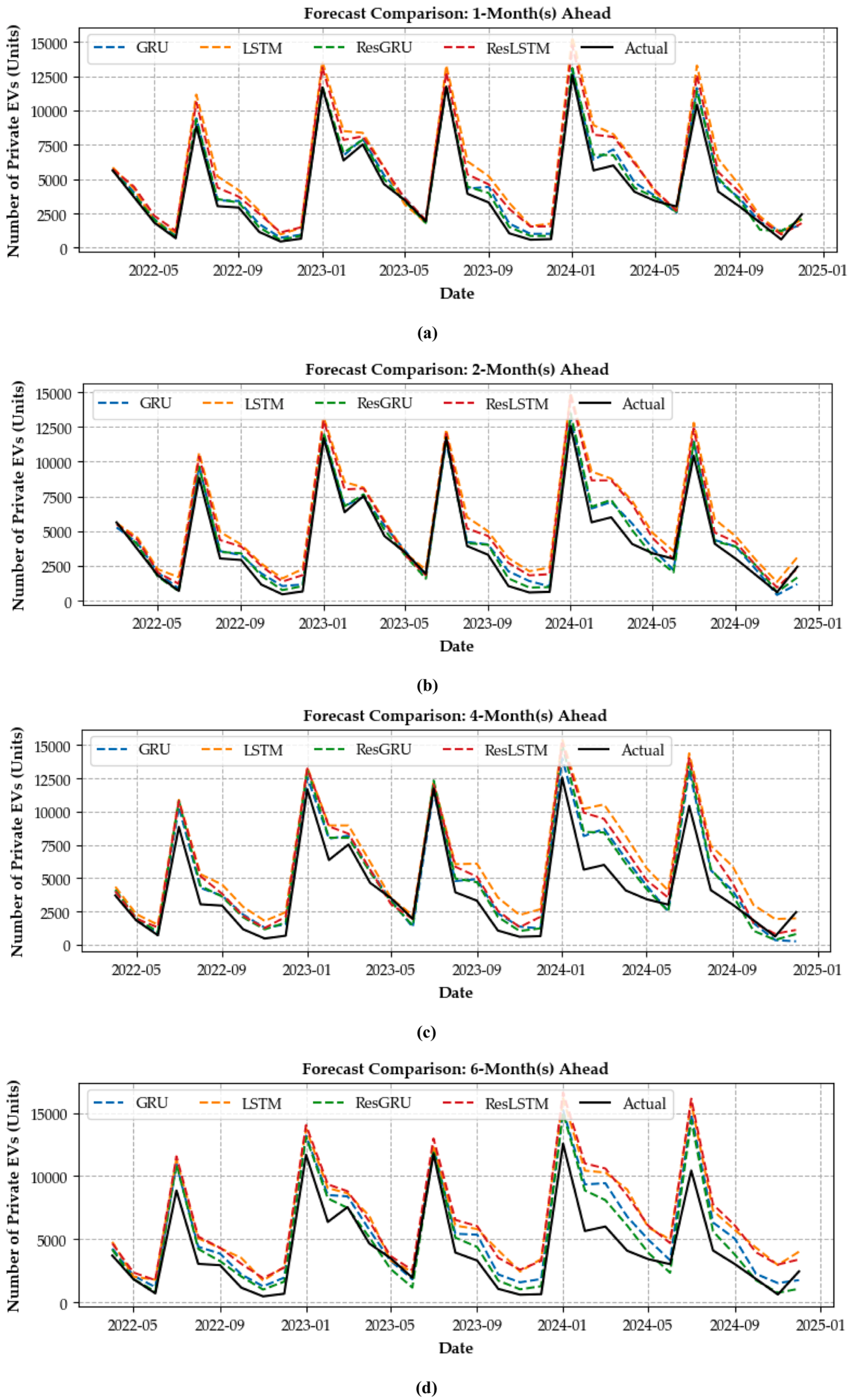


Fig. 13. Forecast of private EV registrations using the proposed MRFO-VMD-ResGRU model in comparison with alternative models; **(a)** 1-month ahead forecast; **(b)** 2-month ahead forecast; **(c)** 4-month ahead forecast; **(d)** 6-month ahead forecast.

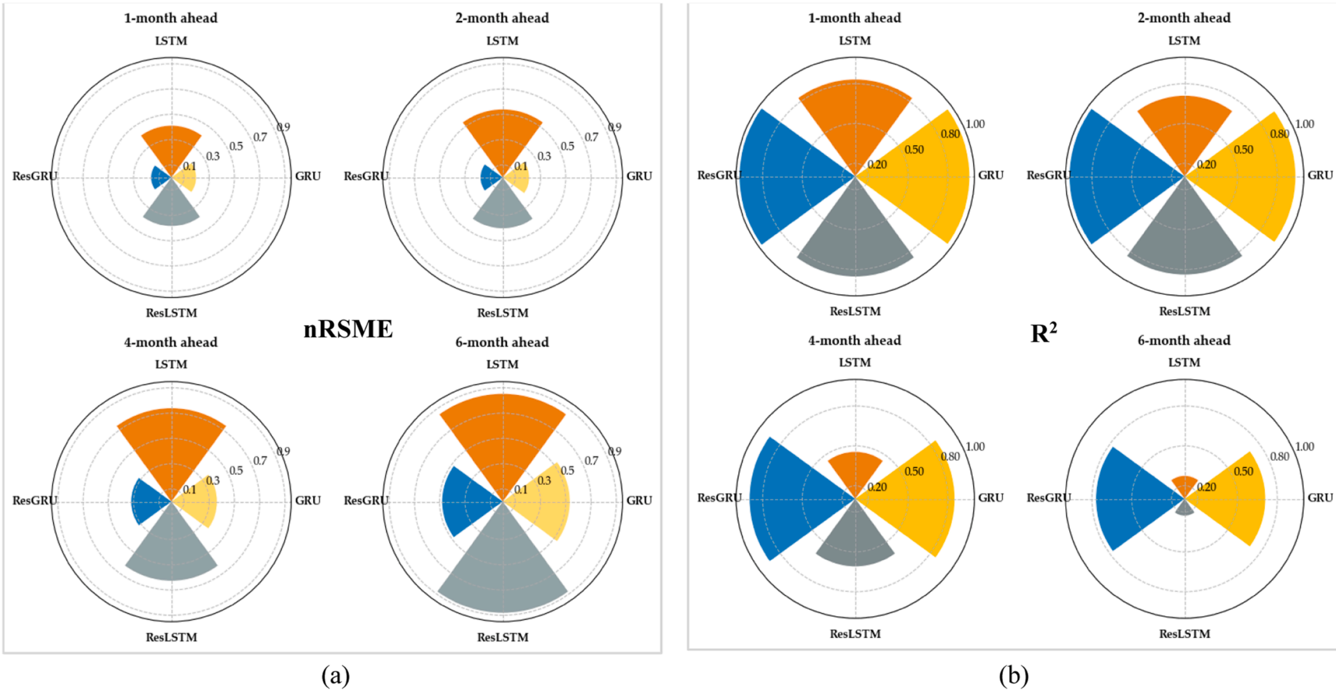


Fig. 14. Performance measures of MRFO-VMD-ResGRU and competitive models across multi-step horizons; (a) radar plots of nRMSE for the 1-, 2-, 4-, and 6-month ahead forecasts; (b) radar plots of R^2 for the 1-, 2-, 4-, and 6-month ahead forecasts.

Table 4
Wilcoxon signed-rank test results.

Horizon (months ahead)	Benchmark	Compared Model	Wilcoxon Statistic	p-value	Decision
T + 1	ResGRU	GRU	198.0	0.067	No Sig. diff
		LSTM	20.0	<0.05	Sig. diff
		ResLSTM	10.0	<0.05	Sig. diff
T + 2	ResGRU	GRU	133.0	<0.05	Sig. diff
		LSTM	9.0	<0.05	Sig. diff
		ResLSTM	56.0	<0.05	Sig. diff
T + 4	ResGRU	GRU	81.0	<0.05	Sig. diff
		LSTM	29.0	<0.05	Sig. diff
		ResLSTM	30.0	<0.05	Sig. diff
T + 6	ResGRU	GRU	67.0	<0.05	Sig. diff
		LSTM	0.0	<0.05	Sig. diff
		ResLSTM	1.0	<0.05	Sig. diff

outweigh the fuel-driven incentives, and resulted in a predicted adoption level that is lower than the baseline value of the model.

(b) Case 2: Post-COVID Recovery and Economic Stability in Ireland (2021)

In this case, a randomly selected instance corresponding to January 2021 in the predicted private EV adoption time series represents the post-COVID-19 period in Ireland, when economic stability had largely resumed. Previous studies also indicated that since the outbreak of COVID-19, public interest in EVs increased markedly (Qian & Gkritza, 2024). Fig. 18b shows the post COVID recovery stage in Ireland, where the W_{avg} reached €42,200, above the mean value across the analysis period. This indicates stronger-than-average purchasing power, and the large positive contribution (+3097.25) reflects a strong capacity for private EV purchase during this stage.

A low $Uemp_r$ of 6.9 % adds another substantial positive effect (+1241.07), which reflects favourable labour market conditions that support major private EV purchases. In addition, a modest rise in the CPI to 107.3, compared to the benchmark period value contributes positively (+682.17) and shows that inflationary pressures were contained while household spending capacity remained high. These combined factors place the predicted adoption level well above the baseline and mark this period as one of the most economically favourable points for Private EV uptake. This trend is also supported by data from SIMI, which show that 8646 new EVs were registered in 2021, more than doubling the 4013 recorded in 2020 (+115.4 %) and representing a 151.0 % increase over the 3444 registered in 2019 (Galway Advertiser, 2022).

(c) Case 3: Mature Phase of the Private EV Market

As the private EV market in Ireland matures, a randomly selected instance from November 2023 shows a prediction strongly driven by GTI. The very high GTI value of 84.97 reflects elevated public awareness, increased information seeking, and stronger public interest, contributing +10,708.22 as the largest positive effect among all factors (Fig. 18c). Higher W_{avg} of €46,000 add a further +3681.71 and reflects a strong purchasing capacity for Private EVs. Elevated P_{Petrol} of 168.2 cent provide a significant positive contribution of +1823.54 and reinforces the economic motivation to shift away from ICEVs. In addition, the phase-out of ICEVs, already nearing the halfway mark ($\Phi_{ICEV} = 0.47$), contributes +1023.41 and shows the influence of policy pressure in accelerating Private EV adoption. Together, these favourable conditions place the predicted Private EV uptake far above the baseline of the model.

3.5. Policy implication

The findings imply that Ireland's EV policy should shift from uniform national subsidies to a diverse support system that takes into account both geographic accessibility and income heterogeneity. The regressive nature of current grants, which mainly benefit higher-income households that already have the financial resources to buy EVs, would be lessened by a tiered purchase support programme that links incentive levels to household income (Ermagun & Tian, 2024; Hu et al., 2025; Stefaniec et al., 2025). Policy priorities should give stronger attention to

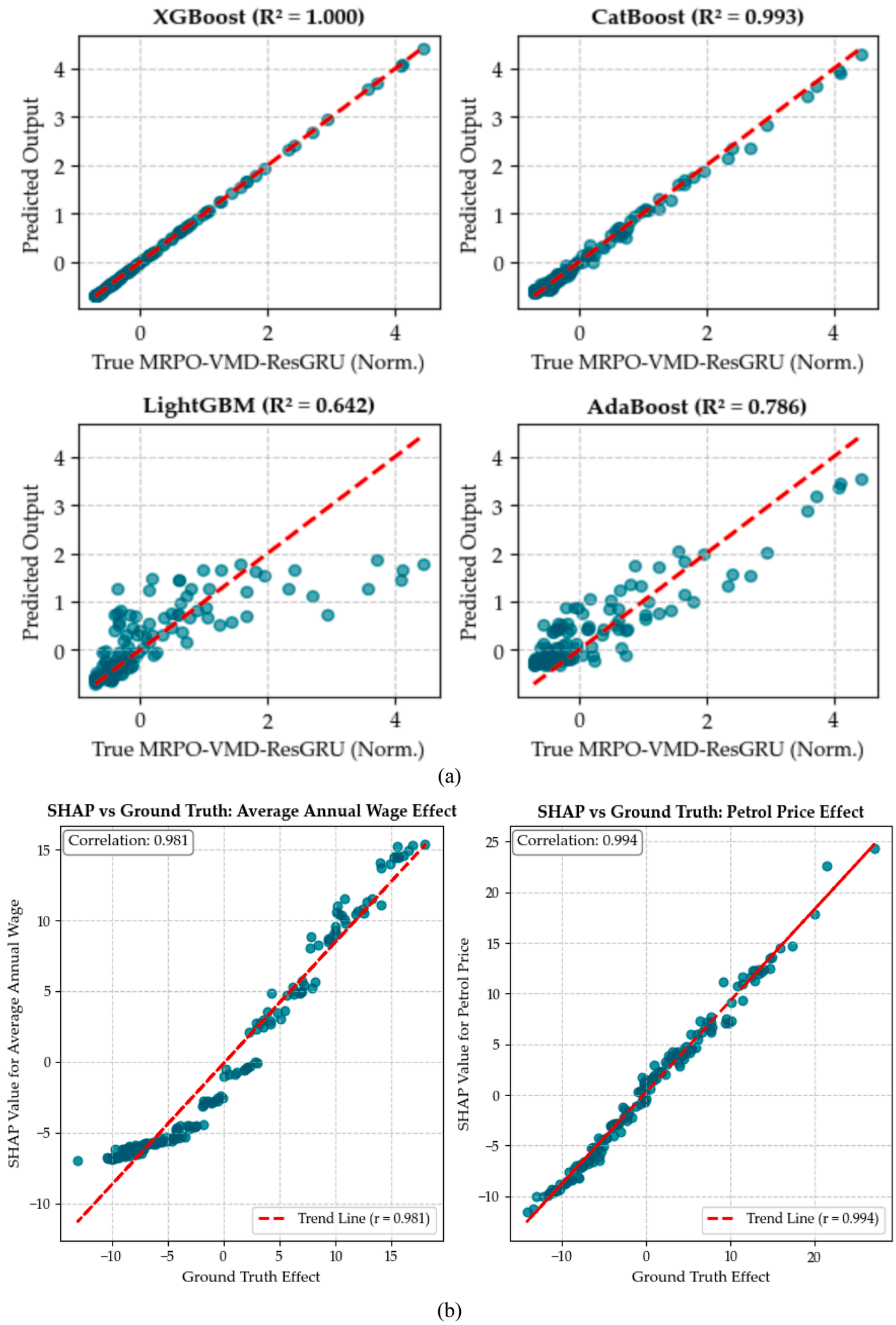


Fig. 15. Surrogate Model Selection and Validation; (a)Surrogate model fidelity (replication accuracy) analysis using XGBoost, CatBoost, LightGBM and AdaBoost; (b) SHAP-ground truth alignment for elasticity testing using the XGBoost surrogate model with Petrol price elasticity effect and average annual wage elasticity effect.

financial support for lower- and middle-income households, along with a deliberate and well-coordinated rollout of high-power charging infrastructure in rural areas where accessibility challenges and range anxiety continue to present significant barriers (Ermagun & Tian, 2024; Hu et al., 2025). Specific price support in conjunction with preferential financing programmes, like state-backed leasing or low-interest green car loans (Bena et al., 2023; Kennedy et al., 2020), would significantly decrease the effective entry barrier for lower- and middle-income groups.

Although EV-specific finance already exists in Ireland, such as a scheme that provides BEVs loans for up to six years at a preferential interest rate of about 5.85 % APR, this type of commercial credit remains inaccessible for many lower-income households because it still requires sufficient creditworthiness and repayment capacity. At the same time, policy design should explicitly integrate spatial equity by directing capital investment toward high-power public charging hubs in rural and peripheral regions where adoption remains constrained by travel needs (Pan et al., 2025). Expanding rural charging networks would not only address geographic disparities but also build confidence among potential adopters whose travel needs require reliable long-distance capability (Charly et al., 2023; Illahi et al., 2024b).

Internet browsing habits can serve as an accurate gauge of aggregate

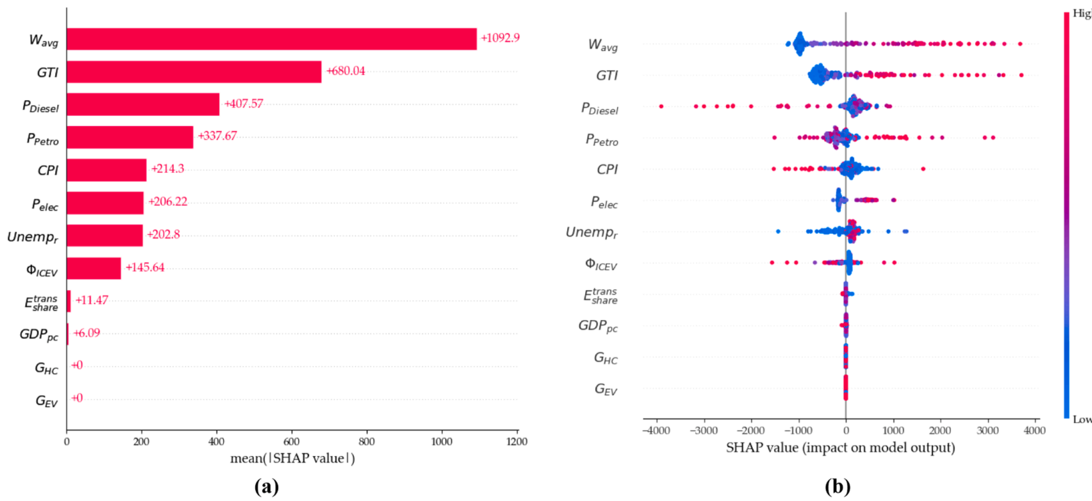


Fig. 16. SHAP interpretation using XGBoost as a surrogate for the proposed MRFO-VMD-ResGRU model; (a) Mean absolute SHAP values for each feature; (b) SHAP summary plot showing the direction and magnitude of each feature's impact on the forecasted Private EV values.

consumer behavior in emerging markets (Carrière-Swallow & Labbé, 2013). Therefore, the prominence of the GTI in this study indicates that behavioral and informational instruments should form a central pillar of the private EV transition strategy in Ireland. Changes in consumer psychology that arise from media attention and online exposure can shift attitudes toward pro-environmental transport choices (Broadbent et al., 2021; Zhao et al., 2024b). Higher visibility of EVs increases perceived relevance and social acceptance. Public awareness policies should therefore move beyond generic promotion toward data-driven engagement that responds to concerns about cost, range, charging reliability, and long-term value (Gupta et al., 2024; Singh & Paul, 2023). Greater public awareness of the environmental benefits of EVs increases the likelihood of their adoption, as higher understanding of emission reduction and sustainability advantages strengthens consumer willingness to shift toward electric mobility (Fitzpatrick, 2025; Zhang et al., 2022).

Digital monitoring of search behavior and social media discourse would permit policymakers to detect shifts in public sentiment in near real time and adjust communication strategies accordingly (Yue et al., 2022). Campaigns that clearly articulate private EV operating cost savings, emission reductions, and improvements in energy efficiency can reinforce the economic signals from fuel prices and carbon policy, which otherwise remain weak in the absence of active consumer attention (Connolly et al., 2023). Integrating financial incentives with sustained public engagement would create a mutually reinforcing policy mix that supports both willingness and ability to adopt EVs across different income groups and regions.

4. Conclusions and future work

In this study, a two-phase framework was developed to forecast private EV adoption in Ireland and to assess the influence of key economic, energy, and behavioral factors. In the first phase, the MRFO VMD ResGRU model was applied to generate multi-horizon projections for 1-, 2-, 4-, and 6-month horizons that represent short-, medium-, and long-term outlooks, where predictive accuracy is higher at shorter horizons and declines gradually as the lead time increases. Comparative evaluation within the same architectural family including MRFO-VMD-GRU, MRFO-VMD-LSTM, and MRFO-VMD-ResLSTM supported by performance measures and the Wilcoxon statistical significance test, shows that MRFO-VMD-ResGRU provides the strongest and most stable performance across the full range of forecast horizons. For the 1-month short-term horizon, MRFO-VMD-ResGRU and MRFO-VMD-GRU exhibit no statistically significant difference in accuracy, which indicates that both models are equally suitable for short-term EV adoption forecasting. However, as the horizon extends to the medium and longer terms, MRFO-VMD-ResGRU shows statistically lower prediction errors than the other variants, which confirms its advantage for capturing the more complex and evolving dynamics of private EV adoption over time.

In the second phase, SHAP-based interpretation was implemented with XGBoost as a surrogate model to explain the forecasts produced by the MRFO-VMD-ResGRU framework. The surrogate model achieved near-perfect fidelity and passed the feature-injection validation, which confirms the reliability of the attribution results. The analysis identifies annual average wage and the GTI as the most influential drivers of private EV adoption, followed by petrol price. In contrast, higher diesel prices show a negative marginal effect, which likely reflects the mobility patterns of rural and long-distance households and the constraint imposed by limited public charging access. Case-based analysis across the early market stage, the post-COVID-19 recovery period, and the mature market phase further reveals a transition in dominant drivers, shifting from constraints linked to low income and limited awareness toward factors driven by rising incomes, lower unemployment, and evolving fuel price dynamics.

4.1. Limitations of the study

Several limitations should be considered when interpreting the results of this study.

1. The EV market in Ireland remains at an early stage of development, and although registrations began in 2010, meaningful adoption only became evident within the last decade, which leaves a relatively short effective data span for model training. This limited historical depth restricts the reliability of long-range projections, and the decline in forecast accuracy at longer horizons, such as the 6-month ahead case, reflects this constraint. As EV adoption continues to expand and longer time series become available, future studies will be able to generate more stable long-term projections and assess structural changes in adoption behavior with greater confidence.
2. Although this study represents the first attempt in Ireland to develop a simultaneous forecasting and explainable assessment framework for private EV adoption, the analysis relies on national-level data. This aggregation masks important heterogeneity between low- and high-income households and between urban and rural regions, where charging access, travel patterns, and

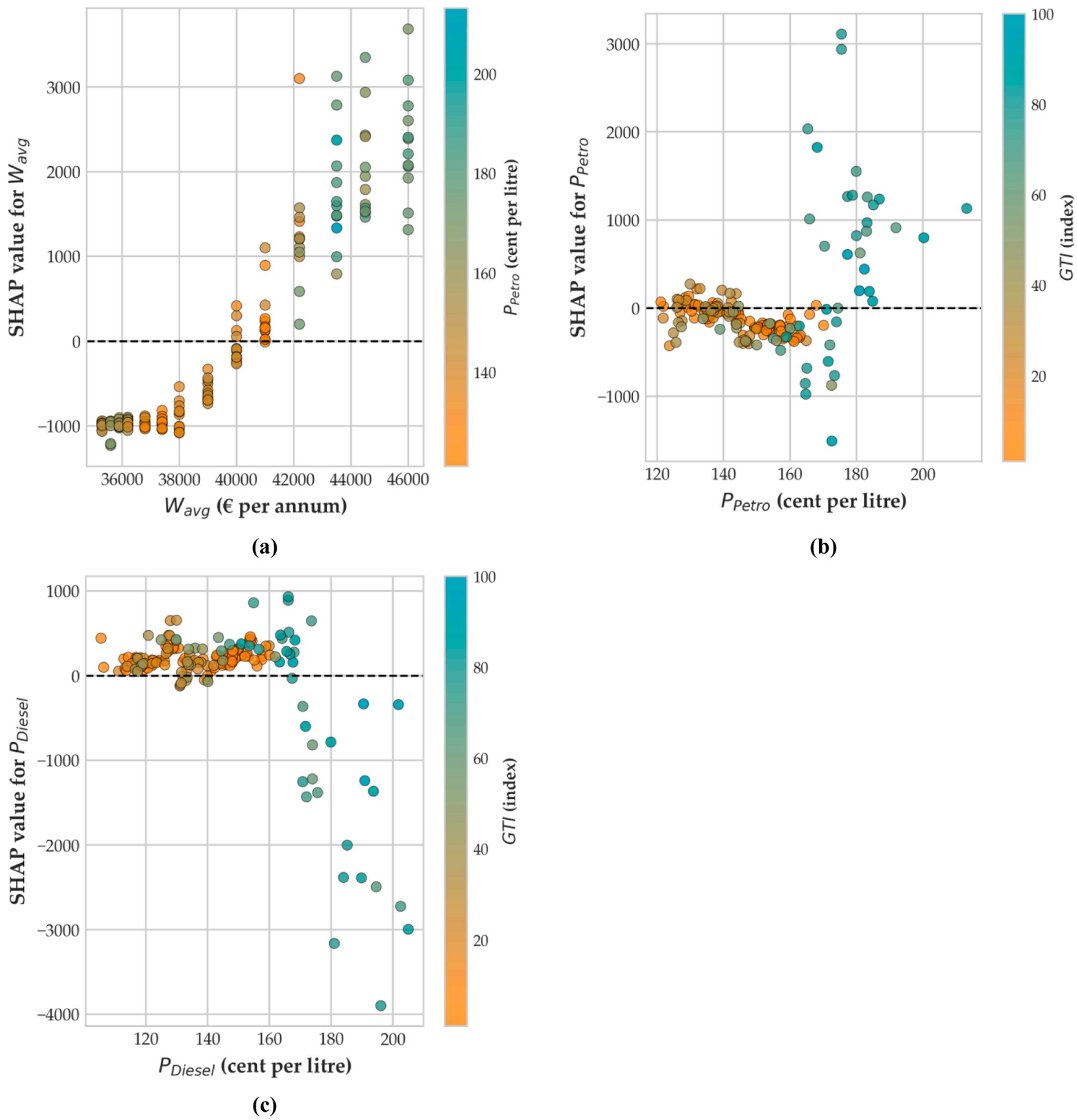


Fig. 17. SHAP dependence plots for the top features **(a)** Combine effect of average annual wage and petrol price, (b) Combine impact of petrol price and GTI; **(c)** Combine impact of diesel price and GTI.

affordability constraints differ substantially. Prior research has highlighted strong regional disparities in EV uptake across Ireland, which indicated that county- or local-authority-level data would permit more precise identification of spatial barriers and policy needs (Prakash et al., 2025; Stefaniec et al., 2025).

3. This study does not distinguish between different private EV makes, models, or vehicle segments. Incorporating model-level sales data would allow future research to examine how technology attributes and price tiers interact with income, fuel prices, and infrastructure availability to shape adoption dynamics.

4.2. Future recommendation

Future studies should jointly model the private EV adoption time series with the phase-out trajectories of private ICEVs in order to assess the dynamic interaction between technology substitution, market saturation, and policy-driven transition pathways. Such a coupled framework would permit more realistic evaluation of how private EV growth accelerates as ICEV registrations decline, which remains critical for long-term transport decarbonisation planning. Similarly, more advanced deep learning architectures should also be explored. Transformer-based models, together with attention-driven temporal networks, could better capture long-range dependencies, regime shifts, and nonlinear dynamics that arise as the private EV market evolves. These models may be combined with signal-processing strategies such as optimized mode decomposition, wavelet analysis, or empirical mode decomposition to enhance stability and interpretability under non-stationary adoption patterns.

Future work should also expand the explanatory feature set beyond the variables considered in this study. Additional factors such as charging-station density, fast-charger availability, electricity tariffs, housing type, dwelling tenure, vehicle ownership per household, second-hand private EV imports, and regional policy interventions could further improve both forecasting accuracy and behavioral interpretation. Incorporating spatially disaggregated data at county or local-authority level would allow future studies to quantify urban–rural disparities and design more targeted infrastructure and subsidy strategies.

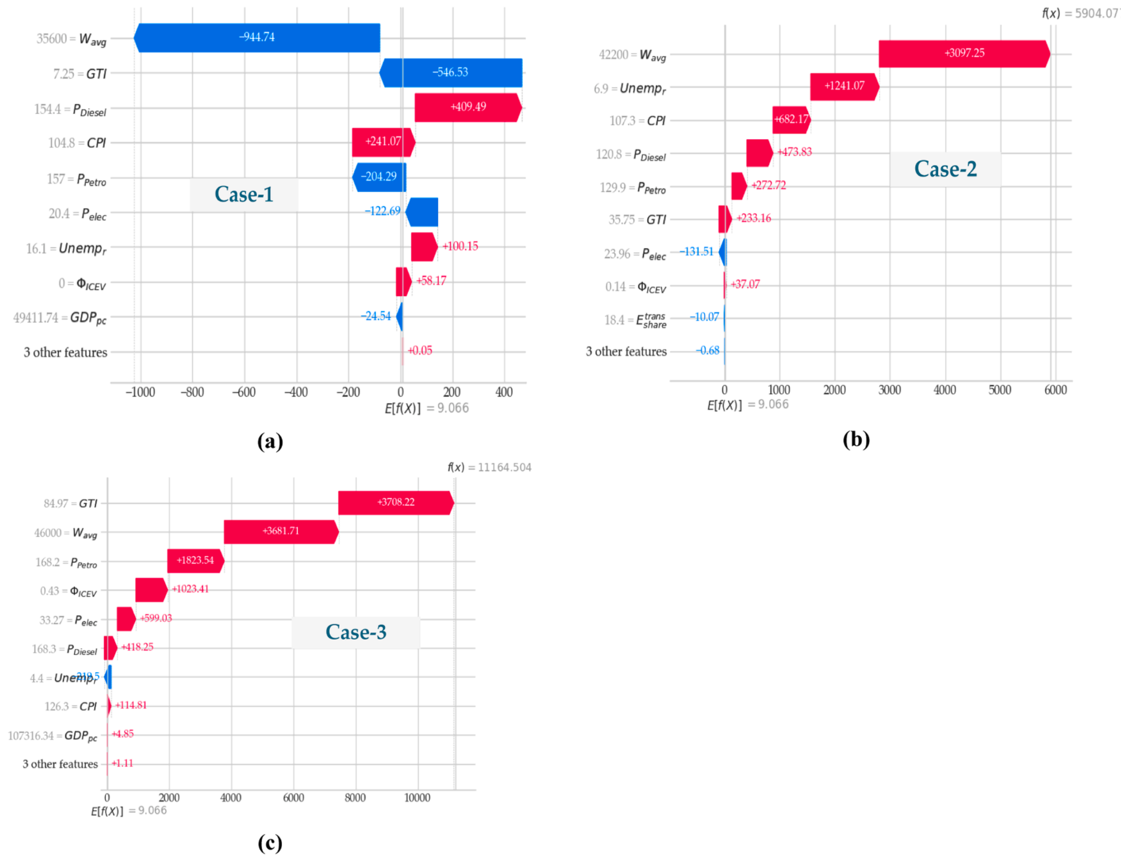


Fig. 18. SHAP local interpretation for three representative prediction cases; (a) Early premature phase of private EV adoption in Ireland; (b) Post-COVID recovery and economic stability phase in Ireland; (c) Mature phase of the private EV market.

CRediT authorship contribution statement

Afaq Khattak: Writing – original draft, Methodology, Investigation, Formal analysis, Conceptualization. **Brian Caulfield:** Validation, Supervision, Project administration, Funding acquisition, Data curation, 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.

Acknowledgments

The authors would like to acknowledge the support of the SEAI National Energy Research Funding Programme for the RATE project (Project code: RDD932) related to the Irish Car Stock modelling. We would like to acknowledge the use of the Grammarly AI tool solely for checking the grammar of this paper.

Appendix A

Fig. A1, Fig. A2, Fig. A3, Fig. A4, Fig. A5, Fig. A6.
Table A1, Table A2, Table A3.

In Ireland, the Average Annual Wage (W_{avg}) exhibited a gradual upward trajectory from 2010 to 2024, corresponding to an average annual growth rate of 1.98 %. Over the same period, the Unemployment Rate $(Uemp_r)$ remained relatively high in 2011 and 2012, at approximately 15 % and 15.5 %, respectively. This was followed by a sustained decline, with the rate reaching about 5 % by 2019. During the COVID-19 period, the $Uemp_r$ increased to around 6.5 % in 2021, before returning to lower levels of approximately 4.5 % by 2024 (CSO, 2024a). The GDP per capita (GDP_{pc}) showed moderate year-to-year change from 2010 onward and exceeded €100,000 from 2021 onwards. Similarly, the Consumer Price Index (CPI) showed limited change between 2010 and 2019, followed by a rapid increase from 2021 onward. Government incentives including EV Purchase Grant (G_{EV}) and Home Charger Grant (G_{HC}) were taken into account. Energy costs further shaped adoption. P_{Petrol} and P_{Diesel} fluctuated, spiking in 2022, while P_{Elec} remained stable until 2020 before rising steadily to their highest level in 2024 (Fig. 14). In case of emissions, the transport sector's emission share (E^{trans}_{share}) increased to 21.4 % by 2023.

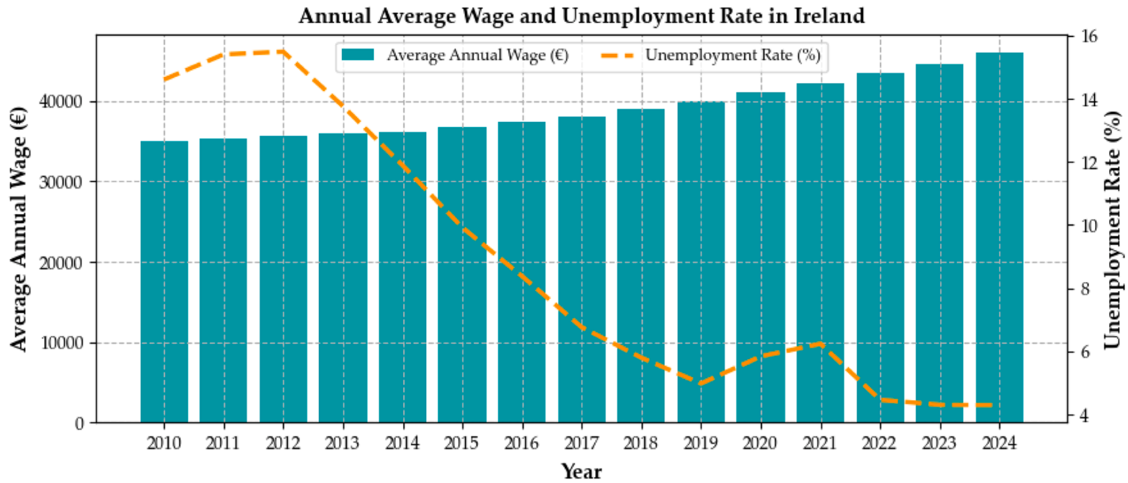


Fig. A1. Annual average wage and unemployment rate in Ireland (2010–2024).

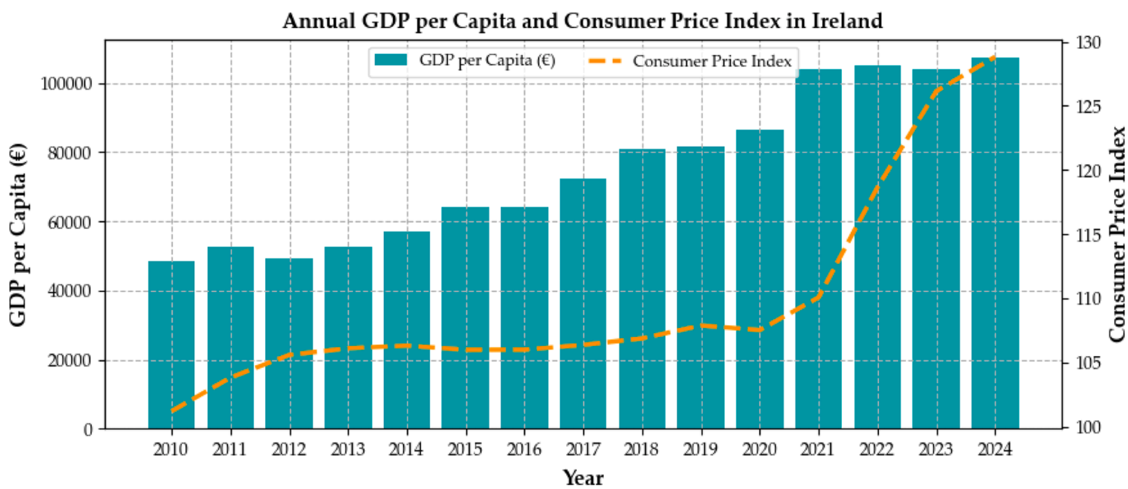


Fig. A2. Annual GDP per capita and CPI in Ireland (2010–2024).

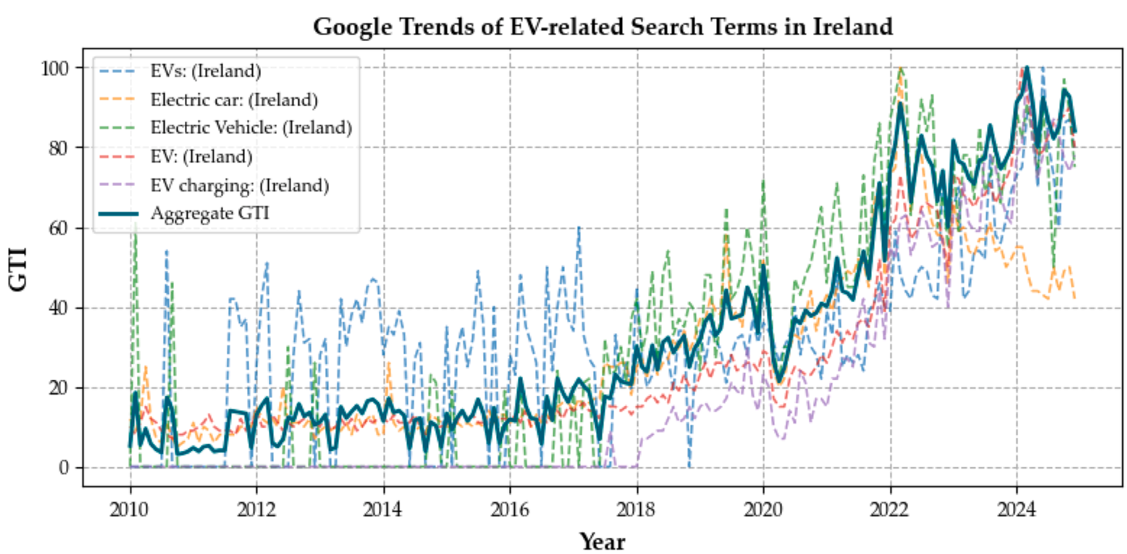


Fig. A3. GTI of EV-related search terms in Ireland from 2010–2024.

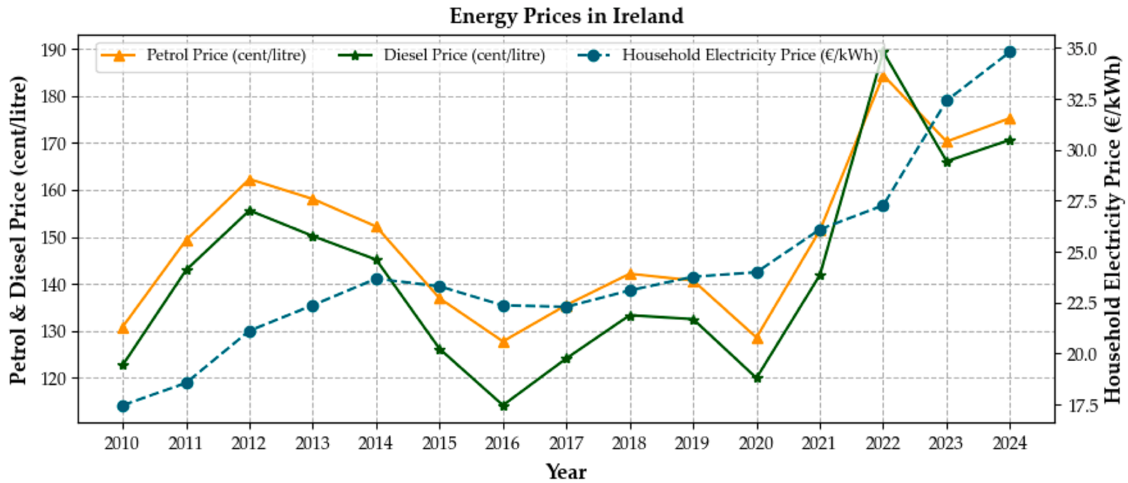


Fig. A4. Energy prices in Ireland from 2010 to 2024.

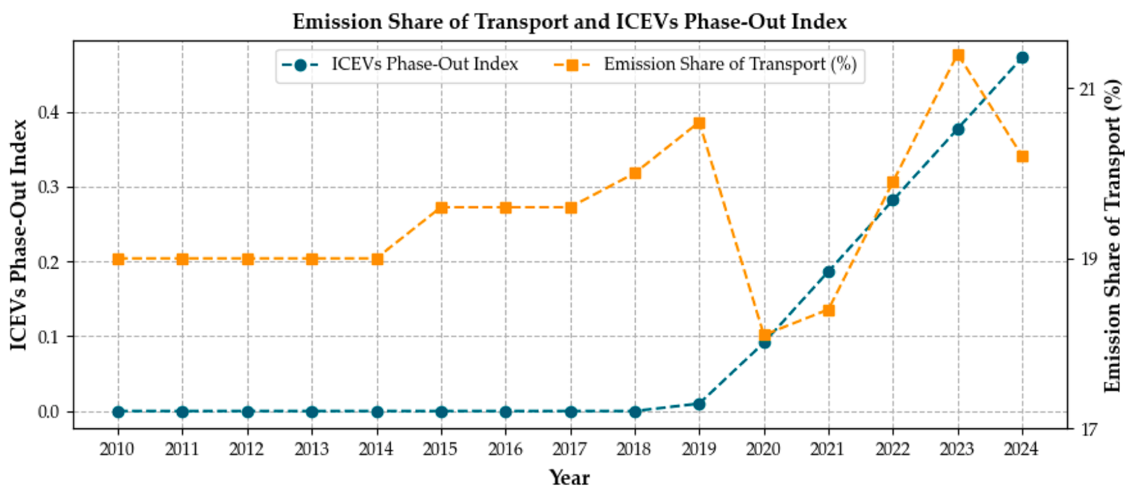


Fig. A5. Emission share of transport and ICEVs phase-out index from 2010 to 2024.

Table A1
Pseudo-code of the MRFO-VMD procedure.

ALGORITHM	MRFO-VMD
	INPUT: $f(t)$: Time series signal of length T, $[\alpha_{\min}, \alpha_{\max}]$: Search bound for α, $[K_{\min}, K_{\max}]$: Search bound for K, P : Population size, I_{max} : Maximum Iteration, $\Gamma(\Theta)$: Fitness function search space Θ
	Initialize Population $\{\Theta_i = (\alpha_i, K_i)\}_{i=1}^{P}$
	for $i = 1$toP **do**
	$\{u_k^{(i)}(t)\}_{k=1}^{K_i} \leftarrow VMD(f(t), \Theta_i)$
	$\Gamma_i \leftarrow \Gamma(\Theta_i)$
	end for
	$\Theta^* \leftarrow \arg\min_i \Gamma_i, \Gamma^* \leftarrow \min_i \Gamma_i$
	for $i = 1$to$I_{\max}$ **do**
	for $i = 1$toP **do**
	$\Theta_i \leftarrow \Theta_i + r_1 \cdot (\Theta_{i-1} - \Theta_i)$ //Chain Foraging
	$\Theta_i \leftarrow \Theta_i \cdot e^{\frac{-i}{I_{max}}} + r_2 \cdot (\Theta^* - \Theta_i)$ //Cyclone Foraging
	$\Theta_i \leftarrow \Theta_i + S \cdot (r_3 \cdot \Theta^* - r_4 \cdot \Theta_i)$ //Somersault Foraging
	$\Theta_i \leftarrow \mathrm{clip}(\Theta_i, [\alpha_{\min}, \alpha_{\max}], [K_{\min}, K_{\max}])$
	$\{u_k^{(i)}(t)\}_{k=1}^{K_i} \leftarrow VMD(f(t), \Theta_i)$
	$\Gamma_i \leftarrow \Gamma(\Theta_i)$
	if $\Gamma_i < \Gamma(\Theta_i)$ **then**
	$\Theta^* \leftarrow \arg\min_i \Gamma_i, \Gamma^* \leftarrow \min_i \Gamma_i,$
	end if
	end for
	end for
	$\{u_k(t)\}_{k=1}^{K^*} \leftarrow VMD(f(t), \Theta^*)$
	RETURN:$\Theta^*, \{u_k(t)\}$

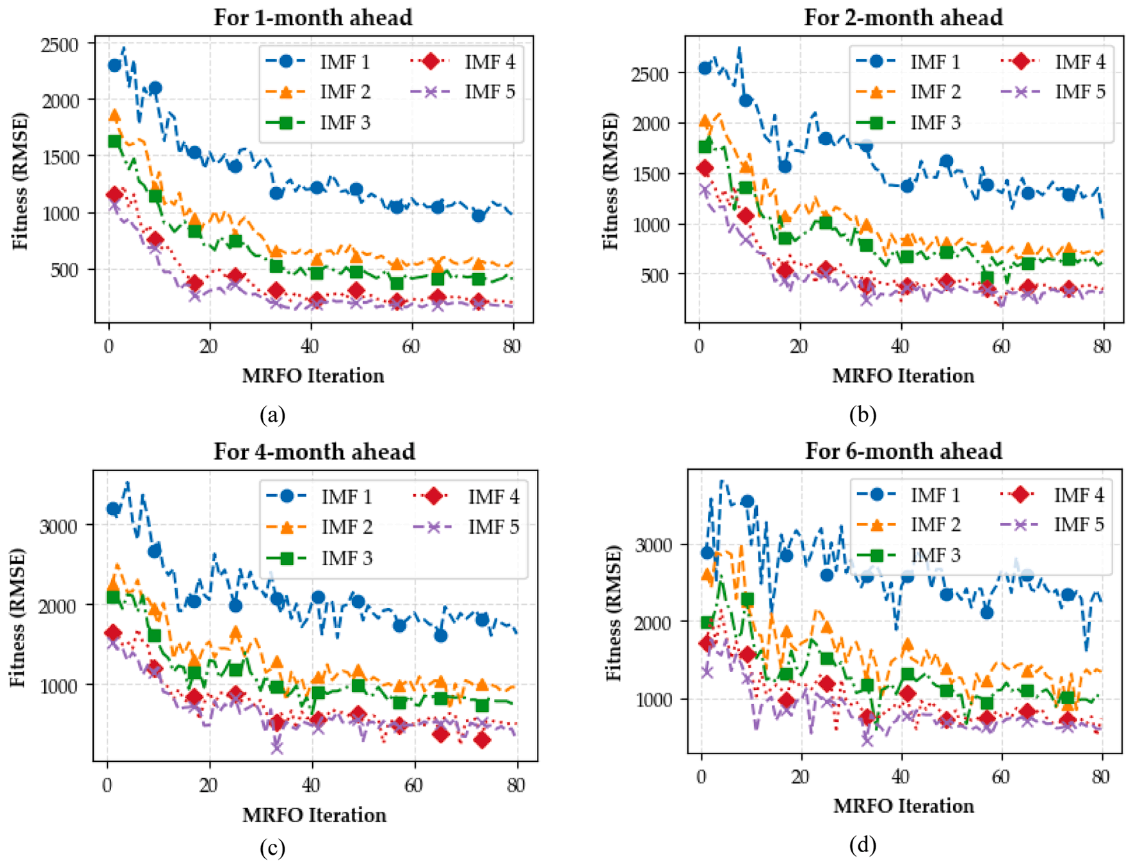


Fig. A6. MRFO fitness evolution for ResGRU hyperparameter search; (a)T + 1 horizon; (b) T + 2; (c) horizon;T + 4 horizon; (d) T + 6 horizon.

Table A2
Optimal GRU hyperparameters for each IMF across forecast horizons.

Parameters	Range	Horizon	Optimal values				
			IMF1	IMF2	IMF3	IMF4	IMF5
Learning rate	0.0001–0.1	T + 1	0.0124	0.0047	0.0216	0.0079	0.0153
		T + 2	0.0068	0.0325	0.0102	0.0184	0.0041
		T + 4	0.0273	0.0096	0.0418	0.0052	0.0227
		T + 6	0.0145	0.0561	0.0084	0.0296	0.0069
Hidden units	16–144	T + 1	72	40	96	64	120
		T + 2	48	112	80	136	64
		T + 4	128	56	104	88	72
		T + 6	96	144	64	112	128
Dropout rate	0.01–0.6	T + 1	0.18	0.34	0.09	0.27	0.41
		T + 2	0.06	0.22	0.48	0.15	0.36
		T + 4	0.31	0.08	0.52	0.26	0.14
		T + 6	0.12	0.45	0.19	0.07	0.33
GRU layers	1–4	T + 1	2	2	3	3	2
		T + 2	1	2	2	2	3
		T + 4	2	1	3	1	1
		T + 6	2	2	2	3	1

Table A3
Horizon-wise IMF correlation screening results.

IMF	Forecast Horizon				Mean Corr	Decision	Justification
	T + 1	**T + 2**	**T + 4**	**T + 6**			
IMF 1	0.880	0.743	0.522	0.22	0.591	**Exclude**	Strong monotonic decay and loss of predictive relevance
IMF 2	0.989	0.948	0.906	0.896	0.935	Retain	High and stable correlation
IMF 3	0.985	0.981	0.964	0.963	0.973	Retain	Consistent and strong predictive association
IMF 4	0.994	0.988	0.978	0.972	0.983	Retain	Strongest and most stable IMF across horizons
IMF 5	0.989	0.987	0.966	0.944	0.972	Retain	Stable long-horizon predictive behavior

Data availability

Data will be made available on request.

References

Abas, P. E., & Tan, B. (2024). Modeling the impact of different policies on electric vehicle adoption: An investigative study. *World Electric Vehicle Journal, 15*(2), 52.
Abualigah, L. (2024). *Metaheuristic optimization algorithms: Optimizers, analysis, and applications*. Morgan Kaufmann.
Abualigah, L., Mahadeen, F., Ezugwu, A. E., Aldiabat, K., Al-diabat, M., Izci, D., Hussein, A. M., Zhang, P., & Şahin, C. B. (2024). A survey of the manta ray foraging optimization algorithm. *Metaheuristic optimization algorithms* (pp. 193–203). Elsevier.
Alam, G. M. I., Arfin Tanim, S., Sarker, S. K., Watanobe, Y., Islam, R., Mridha, M., & Nur, K. (2025). Deep learning model based prediction of vehicle CO2 emissions with eXplainable AI integration for sustainable environment. *Scientific Reports, 15*(1), 3655.
Alsulami, B. T., & Khattak, A. (2025). Integrated OVMD-BiGRU-SMAC framework for forecasting construction accidents in the Kingdom of Saudi Arabia. *IEEE access : Practical innovations, open solutions*.
Arbeláez Vélez, A. M. (2024). Environmental impacts of shared mobility: A systematic literature review of life-cycle assessments focusing on car sharing, carpooling, bikesharing, scooters and moped sharing. *Transport Reviews, 44*(3), 634–658.
Ayyadi, S., & Maaroufi, M. (2018). Diffusion models for predicting electric vehicles market in Morocco. In *2018 International Conference and Exposition on Electrical And Power Engineering (EPE)* (pp. 0046–0051). IEEE.
Bacanin, N., Stoean, C., Zivkovic, M., Rakic, M., Strulak-Wójcikiewicz, R., & Stoean, R. (2023). On the benefits of using metaheuristics in the hyperparameter tuning of deep learning models for energy load forecasting. *Energies, 16*(3), 1434.
Bena, J., Bian, B., & Tang, H. (2023). Financing the global shift to electric mobility. In *Working paper*.
Bodria, F., Giannotti, F., Guidotti, R., Naretto, F., Pedreschi, D., & Rinzivillo, S. (2023). Benchmarking and survey of explanation methods for black box models. *Data Mining and Knowledge Discovery, 37*(5), 1719–1778.
Broadbent, G. H., Wiedmann, T. O., & Metternicht, G. I. (2021). Electric vehicle uptake: Understanding the print media's role in changing attitudes and perceptions. *World Electric Vehicle Journal, 12*(4), 174.
Bushnell, J. B., Muehlegger, E., & Rapson, D. S. (2022). *Energy prices and electric vehicle adoption*. National Bureau of Economic Research.
Carrière-Swallow, Y., & Labbé, F. (2013). Nowcasting with Google Trends in an emerging market. *Journal of Forecasting, 32*(4), 289–298.
CarsForSaleDonegal.ie. (2025). *Guide to electric car prices 2025*.
Castellacci, F., & Santoalha, A. (2025). Does digitalisation affect the adoption of electric vehicles? New regional-level evidence from Google Trends data. *Regional Studies, 59*(1), Article 2358829.
Caulfield, B., Furszyfer, D., Stefaniec, A., & Foley, A. (2022). Measuring the equity impacts of government subsidies for electric vehicles. *Energy, 248*, Article 123588.
Çetin, B., & Taşdemir, Ç. (2024). Forecasting electric vehicle sales using optimized SARIMA model: A two-year predictive analysis. *Veri Bilimi, 7*(2), 41–51.
Chamberlin, G. (2010). Googling the present. *Economic & Labour Market Review, 4*(12), 59–95.
Charly, A., Thomas, N. J., Foley, A., & Caulfield, B. (2023). Identifying optimal locations for community electric vehicle charging. *Sustainable Cities and Society, 94*, Article 104573.
Connolly, R., Pierce, G., Liu, B., 2023. Beyond incentives: Lessons from a community outreach campaign supporting electric vehicle purchase uptake.
CSO. (2024a). *Earnings analysis using administrative data sources 2023*. Central Statistics Office.
CSO. (2024b). *Vehicles licensed for the first time Central Statistics Office*.
Cui, X. (2024). A time series forecasting model based on machine learning. In *2024 IEEE 6th International Conference on Power, Intelligent Computing and Systems (ICPICS)* (pp. 226–230). IEEE.
Dhankhar, S., Dhankhar, N., Sandhu, V., & Mehla, S. (2024). Forecasting electric vehicle sales with arima and exponential smoothing method: The case of india. *Transportation in Developing Economies, 10*(2), 32.
Domarchi, C., & Cherchi, E. (2023). Electric vehicle forecasts: A review of models and methods including diffusion and substitution effects. *Transport reviews, 43*(6), 1118–1143.
Dong, S., Khattak, A., Ullah, I., Zhou, J., & Hussain, A. (2022). Predicting and analyzing road traffic injury severity using boosting-based ensemble learning models with SHAPley Additive exPlanations. *International Journal of Environmental Research and Public Health, 19*(5), 2925.
Du, R. Y., & Hsieh, T.-Y. (2023). Leveraging online search data as a source of marketing insights. *Foundations and Trends® in Marketing, 17*(4), 227–291.
Du, Z., Zhang, G., & Lin, B. (2024). Exploring vehicle preference dynamics: Analyzing the influence of oil price volatility on consumer car purchase decisions-A comparative survey experiment. *Energy, 312*, Article 133616.
Ensslen, A., Ringler, P., Jochem, P., Keles, D., & Fichtner, W. (2014). About business model specifications of a smart charging manager to integrate electric vehicles into the German electricity market. In *Sustainable Energy Policy and Strategies for Europe, 14th IAEE European Conference*. International Association for Energy Economics. *October 28-31, 2014*.
EPA. (2024). *Transport greenhouse gas emissions - EPA*.
Ermagun, A., & Tian, J. (2024). Charging into inequality: A national study of social, economic, and environment correlates of electric vehicle charging stations. *Energy Research & Social Science, 115*, Article 103622.
Fei, Y., Qin, P., Chu, Y., Zheng, H., Tan-Soo, J.-S., & Zhang, X.-B. (2025). Does high gasoline price spur electric vehicle adoption? Evidence from Chinese cities. *Energy Economics, 142*, Article 108188.
Fitzpatrick, A.C., 2025. Understanding electric vehicle adoption: The role of information frictions and heterogeneous beliefs. SAFE Working Paper.
GalwayAdvertiser. (2022). Registered electric vehicle sales in Ireland continue to rise in 2021. *Galway advertiser*.
Gan, W., Ma, R., Zhao, W., Peng, X., Cui, H., Yan, J., Duan, S., Wang, L., Feng, P., & Chu, J. (2025). A VMD-LSTNet-attention model for concentration prediction of mixed gases. *Sensors and Actuators B: Chemical, 422*, Article 136641.
Gautam, D., & Bolia, N. (2024). Understanding consumer choices and attitudes toward electric vehicles: A study of purchasing behavior and policy implications. *Sustainable Development, 32*(5), 4895–4915.
Gerber Machado, P., Rodrigues Teixeira, A. C., Moutinho dos Santos, E., & Mouette, D. (2023). Electric vehicles adoption: A systematic review (2016–2020). *Wiley Interdisciplinary Reviews: Energy and Environment, 12*(5), e477.
Gharehchopogh, F. S., Ghafouri, S., Namazi, M., & Arasteh, B. (2024). Advances in manta ray foraging optimization: A comprehensive survey. *Journal of Bionic Engineering, 21*(2), 953–990.
Giansoldati, M., Monte, A., & Scorrano, M. (2020). Barriers to the adoption of electric cars: Evidence from an Italian survey. *Energy Policy, 146*, Article 111812.
GoI. (2019). *Climate action plan 2019*. Ireland: Government of Ireland.
Green Car Stocks, 2022. Google trends reveals record-breaking interest in EVs. Green car stocks, Los Angeles, CA.
Guidotti, R., Monreale, A., Ruggieri, S., Turini, F., Giannotti, F., & Pedreschi, D. (2018). A survey of methods for explaining black box models. *ACM Computing Surveys (CSUR), 51*(5), 1–42.
Guo, Y., Fraser, T., & Silveira, S. (2025). The role of financial incentives in promoting electric light commercial vehicles in the United States. *Energy Policy, 199*, Article 114526.
Gupta, S., Bansal, R., Bankoti, N., Kar, S. K., Mishra, S. K., Kaur, P., & Harichandan, S. (2024). Factors affecting consumer's intention to use electric vehicles: Mediating role of awareness and knowledge. *Journal of Advanced Transportation, 2024*(1), Article 5922430.
Haan, P., Santonja, A., & Zaklan, A. (2025). Effectiveness and heterogeneous effects of purchase grants for electric vehicles. *Environmental and Resource Economics, 88*(1), 185–223.
Halse, A. H., Hauge, K. E., Isaksen, E. T., Johansen, B. G., & Raaum, O. (2025). Local incentives and electric vehicle adoption. *Journal of the Association of Environmental and Resource Economists, 12*(1), 145–180.
Han, H. (2025). Increases in global transportation-induced air pollution mortality and radiative forcing during 1990–2019. *Frontiers in Environmental Science, 13*, Article 1545924.
Han, Z., Chen, X., Miao, K., Wang, X., & Li, Q. (2025). Predicting product information diffusion for sustainable quality management in industry 4.0: An improved Bass model approach. *Scientific Reports, 15*(1), Article 25989.
Hao, Y., Dong, H., Xu, T., & Zhang, Z. (2024). Research on traffic accident severity prediction based on the LightGBM model. *CICTP, 2024*, 2529–2539.
Hao, Z., Liu, M., Ge, X., 2018. Evaluating the effectiveness of health awareness events by google search frequency. *arXiv preprint arXiv:1810.03781*.
Hassija, V., Chamola, V., Mahapatra, A., Singal, A., Goel, D., Huang, K., Scardapane, S., Spinelli, I., Mahmud, M., & Hussain, A. (2024). Interpreting black-box models: A review on explainable artificial intelligence. *Cognitive Computation, 16*(1), 45–74.
Hawkins, T. R., Singh, B., Majeau-Bettez, G., & Strømman, A. H. (2013). Comparative environmental life cycle assessment of conventional and electric vehicles. *Journal of Industrial Ecology, 17*(1), 53–64.
Hu, H., Zhao, D., Zockaie, A., & Ghamami, M. (2025). Growth patterns and factors of electric vehicle charging infrastructure for sustainable development. *Sustainable Cities and Society, 126*, Article 106417.
Hussain, I., Ching, K. B., Uttraphan, C., Tay, K. G., & Noor, A. (2025). Evaluating machine learning algorithms for energy consumption prediction in electric vehicles: A comparative study. *Scientific Reports, 15*(1), Article 16124.
Hussein, A. M., Zhang, P., & Şahin, C. B. (2024). A survey of the manta ray foraging optimization algorithm. *Metaheuristic Optimization Algorithms: Optimizers, Analysis, and Applications*, 193.
IEA. (2023). *Tracking clean energy progress 2023: Transport overview*. International Energy Agency.
IEA. (2025). *Global Ev outlook 2025*. Paris: International Energy Agency.
Illahi, U., Choudhari, T. P., Charly, A., O'Mahony, M., & Caulfield, B. (2024a). Driving green change: Commercial sector adopting electric vehicles in Ireland. *Transportation Research Part D: Transport and Environment, 135*, Article 104398.
Illahi, U., Egan, R., O'Mahony, M., & Caulfield, B. (2024b). Self-reported public fast charging infrastructure demand: What do existing and potential electric vehicle adopters want and where? *Sustainable Cities and Society, 116*, Article 105935.
Jenn, A., Azevedo, I. L., & Ferreira, P. (2013). The impact of federal incentives on the adoption of hybrid electric vehicles in the United States. *Energy Economics, 40*, 936–942.
Jeong, M.-H., Lee, T.-Y., Jeon, S.-B., & Youm, M. (2021). Highway speed prediction using gated recurrent unit neural networks. *Applied Sciences, 11*(7), 3059.
Jnr, B. A. (2024). Developing a decentralized community of practice-based model for on-demand electric car-pooling towards sustainable shared mobility. *Case Studies on Transport Policy, 15*, Article 101136.

Joshi, R., Ghosh, J., Kalani, N., & Tanna, R. L. (2024). Assessment of stacked LSTM, bidirectional LSTM, ConvLSTM2D, and auto encoders LSTM time series regression analysis at ADITYA-U tokamak. *IEEE Transactions on Plasma Science, 52*(7), 2403–2409.

Jun, S.-P., Yoo, H. S., & Choi, S. (2018). Ten years of research change using Google Trends: From the perspective of big data utilizations and applications. *Technological Forecasting and Social Change, 130*, 69–87.

Karman, A., Bronisz, U., Banaś, J., & Miszczuk, A. (2024). Conceptual and methodological specifications. *Regional competitiveness towards climate change: A model-based approach* (pp. 101–146). Springer.

Katipoğlu, O. M. (2024). Integration of extreme learning machines with CEEMDAN and VMD techniques in the prediction of the multiscalar standardized runoff index and standardized precipitation evapotranspiration index. *Natural Hazards, 120*(1), 825–849.

Kennedy, N., Richard, M., Sanchez, E., Waits, A., 2020. EV financing options for low-to-moderate income individuals in Columbus, OH.

Kevan, L. (2019). *Incentives for personal electric vehicle purchase*. Ireland: Department of Public Expenditure and Reform, Government of Ireland.

Khan, W. A., Chung, S.-H., Liu, S. Q., Masoud, M., & Wen, X. (2025). Smoothing and matrix decomposition-based stacked bidirectional GRU model for machine downtime forecasting. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*.

Khattak, A., & Caulfield, B. (2025). Hybrid SARIMA+ BO-LSTM framework for forecasting EV adoption: A road to net-zero in Ireland. *IEEE Access : Practical Innovations, Open Solutions*.

Khattak, A., Chan, P.-w., Chen, F., & H. Almaliki, A. (2025). A hybrid VMD-TPE-TCN framework for wind shear prediction near an airport runway. *Atmosphere, 16*(4), 381.

Khosravi, K., Golkarian, A., & Tiefenbacher, J. P. (2022). Using optimized deep learning to predict daily streamflow: A comparison to common machine learning algorithms. *Water Resources Management, 36*(2), 699–716.

Kim, S.-Y., Kerr, G. H., van Donkelaar, A., Martin, R. V., West, J. J., & Anenberg, S. C. (2025). Tracking air pollution and CO2 emissions in 13,189 urban areas worldwide using large geospatial datasets. *Communications Earth & Environment, 6*(1), 311.

Kim, Y.-G., Lim, H., & Lee, J. (2024). Decarbonizing road transport in Korea: Role of electric vehicle transition policies. *Transportation Research Part D: Transport and Environment, 128*, Article 104084.

Knittel, C. R., & Tanaka, S. (2025). Challenges to expanding ev adoption and policy responses. *Handbook on electricity regulation* (pp. 405–447). Edward Elgar Publishing.

Kontopoulou, V. I., Panagopoulos, A. D., Kakkos, I., & Matsopoulos, G. K. (2023). A review of ARIMA vs. machine learning approaches for time series forecasting in data driven networks. *Future Internet, 15*(8), 255.

Küfeoğlu, S. (2022). SDG-11: Sustainable cities and communities. *Emerging technologies: Value creation for sustainable development* (pp. 385–408). Springer.

Kumar, R. R., Guha, P., & Chakraborty, A. (2022). Comparative assessment and selection of electric vehicle diffusion models: A global outlook. *Energy, 238*, Article 121932.

Lah, O. (2017). Decarbonizing the transportation sector: Policy options, synergies, and institutions to deliver on a low-carbon stabilization pathway. *Wiley Interdisciplinary Reviews: Energy and Environment, 6*(6), e257.

Law, T. H., Yang, K., Guo, B., & Pang, T. Y. (2025). Electric vehicle adoption: Urbanization, income, and inequality effects. *Transportation Research Part D: Transport and Environment, 148*, Article 105031.

Li, J., Wang, X., Yang, X., Zhang, Q., & Pan, H. (2024a). Analyzing freeway safety influencing factors using the CatBoost model and interpretable machine-learning framework, SHAP. *Transportation Research Record, 2678*(7), 563–574.

Li, Q., Ji, Y., Zhu, M., Zhu, X., & Sun, L. (2024b). Unsupervised feature selection using chronological fitting with Shapley Additive explanation (SHAP) for industrial time-series anomaly detection. *Applied Soft Computing, 155*, Article 111426.

Li, S., Zhu, X., Ma, Y., Zhang, F., & Zhou, H. (2022). The role of government in the market for electric vehicles: Evidence from China. *Journal of Policy Analysis and Management, 41*(2), 450–485.

Lindberg, S., & Lee, S. (2017). A unified approach to interpreting model prediction. In *31st Conference on Neural Information Processing Systems (NIPS 2017)*.

Liu, B., Song, C., Liang, X., Lai, M., Yu, Z., & Ji, J. (2023). Regional differences in China's electric vehicle sales forecasting: Under supply-demand policy scenarios. *Energy Policy, 177*, Article 113554.

Liu, C., Peng, Z., Liu, L., & Wu, H. (2024). Analysis of spatiotemporal characteristics and influencing factors of electric vehicle charging based on multisource data. *ISPRS International Journal of Geo-Information, 13*(2), 37.

Liu, X., Goh, H. H., Xie, H., He, T., Yew, W. K., Zhang, D., Dai, W., & Kurniawan, T. A. (2025). ResGRU: A novel hybrid deep learning model for compound fault diagnosis in photovoltaic arrays considering dust impact. *Sensors, 25*(4), 1035.

Ma, H., Kasihmuddin, M. S. M., Mansor, M. A., Jamaludin, S. Z. M., Marsani, M. F., & Rose, F. Z. C. (2025). Hybrid OCSSA-VMD and optimized Deep learning networks for runoff forecasting. *IEEE Access : Practical Innovations, Open Solutions*.

Ma, X., Li, M., Tong, J., & Feng, X. (2023). Deep learning combinatorial models for intelligent supply chain demand forecasting. *Biomimetics, 8*(3), 312.

Makubhai, S. S., Pathak, G. R., & Chandre, P. R. (2023). Exploring the trade-offs between blackbox and explainable AI: A comparative study. In *2023 7th International Conference On Computing, Communication, Control And Automation (ICCUBEA)* (pp. 1–8). IEEE.

Maugeri, A., Barchitta, M., Perticone, V., & Agodi, A. (2023). How COVID-19 pandemic has influenced public interest in foods: A Google Trends analysis of Italian data. *International Journal of Environmental Research and Public Health, 20*(3), 1976.

McElgunn, J., 2018. Consumer awareness of electric vehicles and global purchasing patterns.

MG Motor Ireland, 2025. MG4 EV | MG Motor Ireland.

Micheal, J. (2024). *Accelerating the transition - Understanding and addressing barriers to consumer adoption of tesla electric vehicles*. Cork Institute of Technology.

Miconi, F., & Dimitri, G. M. (2023). A machine learning approach to analyse and predict the electric cars scenario: The Italian case. *PloS One, 18*(1), Article e0279040.

Mishra, R. D., Dash, S. K., Chudjuarjeen, S., Mohanty, S., Gautam, S. P., Mohanty, R., & Tanvir, M. T. (2024). Hybrid LSTM-GBRT based machine learning technique implementation for electric vehicle sales prediction analysis. *International Journal of Sustainable Engineering, 17*(1), 843–858.

Mohamad, M., & Kok, H. S. (2019). Using Google Trends data to study public interest in breast cancer screening in Malaysia. *Asian Pacific Journal of Cancer Prevention: APJCP, 20*(5), 1427.

Molnar, C., 2020. *Interpretable machine learning*. Lulu.Com.

Möring-Martínez, G., Senzeybek, M., & Jochem, P. (2024). Clustering the European Union electric vehicle markets: A scenario analysis until 2035. *Transportation Research Part D: Transport and Environment, 135*, Article 104372.

Muehlegger, E., Rapson, D.S., 2018. Subsidizing mass adoption of electric vehicles: Quasi-experimental evidence from California.

Naseri, H., Waygood, E., Wang, B., & Patterson, Z. (2023). Interpretable machine learning approach to predicting electric vehicle buying decisions. *Transportation Research Record, 2677*(12), 704–717.

Nazarieh, F., & Naderi Dehkordi, M. (2023). Time series forecasting based on a novel ensemble-based network and variational mode decomposition. *Expert Systems, 40*(7), Article e13291.

Ndhlovu, E., Mhlanga, D., & Duri, B. (2025). Decarbonising urban transport: An overview of electric vehicles, public transport, and sustainable infrastructure in achieving net-zero emissions. *Discover Global Society, 3*(1), 53.

Noel, L., de Rubens, G. Z., Kester, J., & Sovacool, B. K. (2020). Understanding the socio-technical nexus of Nordic electric vehicle (EV) barriers: A qualitative discussion of range, price, charging and knowledge. *Energy Policy, 138*, Article 111292.

NTA. (2023). *National household travel survey research report*.

O'Brien, C., & O'Donovan, D. (2024). *Vehicle registration tax (VRT)*. Dublin, Ireland: Irish Tax and Customs.

Odusami, M., Maskeliūnas, R., Damaševičius, R., & Misra, S. (2024). Machine learning with multimodal neuroimaging data to classify stages of Alzheimer's disease: A systematic review and meta-analysis. *Cognitive Neurodynamics, 18*(3), 775–794.

Oruc, S., Hınıs, M. A., Selek, Z., & Tuğrul, T. (2025). Deep signals: Enhancing bottom temperature predictions in Norway's Mjøsa Lake through VMD-and EMD-boosted machine learning models. *Water, 17*(18), 2673.

Paliari, I., Karanikola, A., & Kotsiantis, S. (2021). A comparison of the optimized LSTM, XGBOOST and ARIMA in Time Series forecasting. In *2021 12th international conference on information, intelligence, systems & applications (IISA)* (pp. 1–7). IEEE.

Pamidimukkala, A., Kermanshachi, S., Rosenberger, J. M., & Hladik, G. (2024). Barriers to adoption of electric vehicles in Texas. *Environmental Science and Pollution Research, 31*(11), 16735–16745.

Pan, J., Li, A., Tang, B., Wang, F., Chen, C., Wu, W., & Wei, B. (2025). Comparative analysis of spatial distribution and mechanism differences between public electric vehicle charging stations and traditional gas stations: A case study from Wenzhou, China. *Sustainability, 17*(17), 8009.

Parsa, A. B., Movahedi, A., Taghipour, H., Derrible, S., & Mohammadian, A. K. (2020). Toward safer highways, application of XGBoost and SHAP for real-time accident detection and feature analysis. *Accident Analysis & Prevention, 136*, Article 105405.

Patil, G. J. (2023). *Investigating consumer satisfaction and price sensitivity for electric vehicle charging infrastructure: An Irish case study*. Dublin: National College of Ireland.

Pellegrini, A., Borriello, A., & Rose, J. M. (2023). Assessing the willingness of Australian households for adopting home charging stations for electric vehicles. *Transportation Research Part C: Emerging Technologies, 148*, Article 104034.

Peterson, A. (2024). Evaluating the impact of price fluctuations on consumer buying decisions and adaptation strategies in the automotive market. *Law and Economy, 3*(4), 1–9.

Phillips, B. B., Burgess, K., Willis, C., & Gaston, K. J. (2022). Monitoring public engagement with nature using Google Trends. *People and Nature, 4*(5), 1216–1232.

Prakash, P., Hanafin, J., Sarkar, D., & Olszewska, M. (2025). Accelerating electric vehicle (EV) adoption: A remote sensing data driven and deep learning-based approach for planning public car charging infrastructure. *Remote Sensing Applications: Society and Environment, 37*, Article 101447.

Qian, X., & Gkritza, K. (2024). Spatial and temporal variance in public perception of electric vehicles: A comparative analysis of adoption pioneers and laggards using twitter data. *Transport Policy, 149*, 150–162.

Ramadan, M., Aboalola, D., Aouabdi, S., Alghamdi, T., Alsolami, M., Samkari, A., & Alsiary, R. (2024). Influence of Breast Cancer Awareness Month on public interest of breast cancer in high-income countries between 2012 and 2022: Google Trends analysis. *JMIR Cancer, 10*(1), Article e49197.

Revenue, 2024. Registration plate standards. Revenue.Ie, Ireland.

Rimpas, D., Barkas, D. E., Orfanos, V. A., & Christakis, I. (2025). Decarbonizing the transportation sector: A review on the role of electric vehicles towards the European green deal for the new emission standards. *Air, 3*(2), 10.

Rudin, C. (2019). Stop explaining black box machine learning models for high stakes decisions and use interpretable models instead. *Nature Machine Intelligence, 1*(5), 206–215.

Ruoso, A. C., & Ribeiro, J. L. D. (2022). The influence of countries' socioeconomic characteristics on the adoption of electric vehicle. *Energy for Sustainable Development, 71*, 251–262.

Sadeghvaziri, E., Javid, R., Omidi, H., & Arafat, M. (2024). A machine learning approach to understanding sociodemographic factors in electric vehicle ownership in the US. *Sustainability, 16*(23), Article 10202.

Şahin, E., Arslan, N. N., & Özdemir, D. (2025). Unlocking the black box: An in-depth review on interpretability, explainability, and reliability in deep learning. *Neural Computing and Applications, 37*(2), 859–965.

Sang, Y., Zhang, Z., Liu, S., & Song, C. (2026). Decarbonization pathways in the transport sector: A review of integrated assessment models and future directions for model improvement. *Renewable and Sustainable Energy Reviews, 225*, Article 116204.

Santa-Eulalia, L. A., Neumann, D., & Klasen, J. (2011). A simulation-based innovation forecasting approach combining the bass diffusion model, the discrete choice model and system dynamics-an application in the German market for electric cars. In *The third international conference on advances in system simulation*.

Saraç, M. S., & Ertürk, M. A. (2025). Forecasting the number of electric vehicles in Turkey towards 2030: SARIMA approach. *Energies, 18*(18), 4808.

SEAI. (2020). *Driving purchases of electric vehicles in Ireland*. Dublin: Sustainable Energy Authority of Ireland.

Sheldon, T. L., & Dua, R. (2024). The dynamic role of subsidies in promoting global electric vehicle sales. *Transportation Research Part A: Policy and Practice, 187*, Article 104173.

Sheng, A., Xie, L., Zhou, Y., Wang, Z., & Liu, Y. (2023). A hybrid model based on complete ensemble empirical mode decomposition with adaptive noise, GRU network and whale optimization algorithm for wind power prediction. *IEEE Access : Practical Innovations, Open Solutions, 11*, 62840–62854.

Shil, S. K., Chowdhury, M. S. R., Tannier, N. R., Tarafder, M., Akter, R., Gurung, N., & Sizan, M. M. H. (2024). Forecasting electric vehicle adoption in the USA using machine learning models. *Journal of Computer Science and Technology Studies, 6*(5), 61–74.

SIMI. (2025). *Vehicle registration statistics*. Ireland: Society of the Irish Motor Industry.

Simsek, A. I., Koç, E., Desticioglu Tasdemir, B., Aksöz, A., Turkoglu, M., & Sengur, A. (2024). Deep learning forecasting model for market demand of electric vehicles. *Applied Sciences, 14*(23), Article 10974.

Singh, D., & Paul, U. K. (2023). Impact of awareness on the adoption of electric vehicles: A systematic literature review. *Fostering Sustainable Development in the Age of Technologies*, 331–357.

Somayeh Falahati Khanaman, W. Q., & Lin, Guo (2025). Comparing economic, social, and environmental drivers of electric vehicle sales in the United States and China: A data-driven analysis since 2008. In *Proceedings of the International Conference on Industrial Engineering and Operations Management*.

Stefaniec, A., Egan, R., Hosseini, K., & Caulfield, B. (2025). The challenge of making EVs just affordable enough: Assessing the impact of subsidies on equity and emission reduction in Ireland. *Research in Transportation Economics, 109*, Article 101495.

Su, Y., Wang, Z., Dong, Z., Hua, X., Ye, T., Song, Z., & Shao, Y. (2025). Frequency-aware ultra-short-term wind power forecasting using CEEMDAN-VMD-SE and Transformer-GRU networks. *Energy*, Article 138715.

Sun, Z., Wang, Z., Qi, X., Wang, D., Gu, X., Wang, J., Lu, H., & Chen, Y. (2024). Understanding key contributing factors on the severity of traffic violations by elderly drivers: A hybrid approach of latent class analysis and XGBoost based SHAP. *International Journal of Injury Control and Safety Promotion, 31*(2), 273–293.

Swaroop, A., Virdee, B., Correia, S. D., & Polkowski, Z. (2025). *Proceedings of data analytics and management: ICDAM 2024, 3*. Singapore: Springer Nature.

Tang, Y., Zhou, Y., Liu, P., Luo, Y., Lin, F., & Chang, F.-J. (2025). Revolutionizing solar-hydro-wind power forecasts in regional power systems with hybrid machine learning models. *Solar Energy, 291*, Article 113391.

Timilsina, M. S., Sen, S., Uprety, B., Patel, V. B., Sharma, P., & Sheth, P. N. (2024). Prediction of HHV of fuel by machine learning algorithm: Interpretability analysis using Shapley Additive explanations (SHAP). *Fuel, 357*, Article 129573.

Tripathy, B. K., & Seetha, H. (2024). *Explainable, interpretable, and transparent ai systems*. CRC Press.

Tuli, S., Casale, G., Jennings, N.R., 2022. Tranad: Deep transformer networks for anomaly detection in multivariate time series data. *arXiv preprint arXiv:2201.07284*.

Turrentine, T., Tal, G., Rapson, D., 2018. The dynamics of plug-in electric vehicles in the secondary market and their implications for vehicle demand, durability, and emissions.

Vaidya, H., & Chatterji, T. (2019). SDG 11 sustainable cities and communities: SDG 11 and the new urban agenda: Global sustainability frameworks for local action. *Actioning the global goals for local impact: Towards sustainability science, policy, education and practice* (pp. 173–185). Springer.

Vasconcellos-Silva, P. R., Carvalho, D. B. F., Trajano, V., de La Rocque, L. R., Sawada, A. C. M. B., & Juvanhol, L. L. (2017). Using Google Trends data to study public interest in breast cancer screening in Brazil: Why not a pink February? *JMIR Public Health and Surveillance, 3*(2), e7015.

Veysi, S., Moshfeghi, M., Sadrfaridpour, A., & Emamy, P. (2025). Electric vehicle sales forecast for the UK: Integrating machine learning, time series models, and global trends. *Algorithms, 18*(7), 430.

Virell, K. (2025). *Explainable ml with shap and LIME: Opening the black box of complex models*. Amazon Digital Services LLC - Kdp.

Wang, H., Wang, Y., Liu, Y., & Yao, Y. (2024). Electrocardiogram prediction based on variational mode decomposition and a convolutional gated recurrent unit. *EURASIP Journal on Advances in Signal Processing, 2024*(1), 16.

Wang, K.-H., Su, C.-W., Xiao, Y., & Liu, L. (2022). Is the oil price a barometer of China's automobile market? From a wavelet-based quantile-on-quantile regression perspective. *Energy, 240*, Article 122501.

Wang, K., Yang, T., Kong, S., & Li, M. (2025). Air quality index prediction through TimeGAN data recovery and PSO-optimized VMD-deep learning framework. *Applied Soft Computing, 170*, Article 112626.

Wei, C., Quan, Z., Qian, Z., Pang, H., Su, Y., & Wang, L. (2025). An attention mechanism augmented CNN-GRU method integrating optimized variational mode decomposition and frequency feature classification for complex signal forecasting. *Expert Systems with Applications, 269*, Article 126464.

Wicki, M., Brückmann, G., & Bernauer, T. (2022). How to accelerate the uptake of electric cars? Insights from a choice experiment. *Journal of Cleaner Production, 355*, Article 131774.

Wood, J. (2022). Electric vehicles: The 3 main factors holding back sales. *World Economic Forum*.

Wu, M., & Chen, W. (2022). Forecast of electric vehicle sales in the world and China based on PCA-GRNN. *Sustainability, 14*(4), 2206.

Xia, X., Wang, X., & Chen, W. (2025). Fault diagnosis of wind turbine gearbox based on improved multivariate variational mode decomposition and ensemble refined composite multivariate multiscale dispersion entropy. *Entropy, 27*(2), 192.

Yu, R., Wang, X., Xu, X., & Zhang, Z. (2024). Research on forecasting sales of pure electric vehicles in China based on the seasonal Autoregressive integrated Moving average–Gray relational analysis–Support vector regression model. *Systems, 12*(11), 486.

Yue, A., Mao, C., Chen, L., Liu, Z., Zhang, C., & Li, Z. (2022). Detecting changes in perceptions towards smart city on Chinese social media: A text mining and sentiment analysis. *Buildings, 12*(8), 1182.

Zeng, M., Zhan, X., Xue, S., Ma, M., & Li, Y. (2013). Inventory forecast of electric vehicles in China during the twelfth five-year plan period using bass model optimized by particle swarm optimization. *Journal of Applied Sciences, 13*(21), 4887–4891.

Zhang, H., Irfan, M., Ai, F., Al-Aiban, K. M., & Abbas, S. (2024a). Analyzing barriers to the adoption and development of electric vehicles: A roadmap towards sustainable transportation system. *Renewable Energy, 233*, Article 121136.

Zhang, J., Xu, S., He, Z., Li, C., & Meng, X. (2022). Factors influencing adoption intention for electric vehicles under a subsidy deduction: From different city-level perspectives. *Sustainability, 14*(10), 5777.

Zhang, Y., Zhong, M., Geng, N., & Jiang, Y. (2017). Forecasting electric vehicles sales with univariate and multivariate time series models: The case of China. *PloS One, 12*(5), Article e0176729.

Zhang, Y., Zhong, W., Li, Y., Wen, L., & Sun, X. (2024b). ResGRU: A deep learning approach for settlement prediction in CFRD based on the spatiotemporal feature fusion method. *Computers and Geotechnics, 173*, Article 106518.

Zhao, W., Zhang, Z., & Wang, L. (2020). Manta ray foraging optimization: An effective bio-inspired optimizer for engineering applications. *Engineering Applications of Artificial Intelligence, 87*, Article 103300.

Zhao, X., Hu, H., Yuan, H., & Chu, X. (2023). How does adoption of electric vehicles reduce carbon emissions? Evidence from China. *Heliyon, 9*(9), Article E20296.

Zhao, X., Li, X., Jiao, D., Mao, Y., Sun, J., & Liu, G. (2024a). Policy incentives and electric vehicle adoption in China: From a perspective of policy mixes. *Transportation Research Part A: Policy and Practice, 190*, Article 104235.

Zhao, X., Li, X., Wang, A., & Fang, J. (2025). The impact of energy prices on electric vehicle adoption: From a perspective of consumer expectations. *Sustainable Futures, 9*, Article 100437.

Zhao, X., Li, X., Zhao, Z., & Luo, T. (2024b). Media attention and electric vehicle adoption: Evidence from 275 cities in China. *Transportation Research Part A: Policy and Practice, 190*, Article 104269.

Zhao, Y., & Ma, J. (2025). Faithful and interpretable explanations for complex ensemble time series forecasts using surrogate models and forecastability analysis. In *31st ACM SIGKDD Conference on Knowledge Discovery and Data Mining*. Association for Computing Machinery.

Zhou, J., Khattak, A., Mao, X., Chen, F., Xing, L., & Zhang, Z. (2025). Hybrid signal decomposition and deep learning framework for vehicle–vehicle crash forecasting. *Scientific Reports, 15*(1), Article 37961.