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Revealing drivers of green technology adoption through explainable Artificial Intelligence

Dorothea Kistinger [a,b], Maurizio Titz [c,d], Philipp C. Böttcher [c], Michael T. Schaub [a], Sandra Venghaus [e,f,*], Dirk Witthaut [c,d,**]

[a] Department of Computer Science, RWTH Aachen University, 52074 Aachen, Germany
[b] Potsdam Institute for Climate Impact Research (PIK), Member of the Leibniz Association, P.O. Box 60 12 03, 14412 Potsdam, Germany
[c] Institute of Climate and Energy Systems: Energy Systems Engineering (ICE-1), Forschungszentrum Jülich, 52428 Jülich, Germany
[d] Institute for Theoretical Physics, University of Cologne, 50937 Köln, Germany
[e] School of Business and Economics, RWTH Aachen University, 52072 Aachen, Germany
[f] Institute of Climate and Energy Systems: Jülich Systems Analysis (ICE-2), Forschungszentrum Jülich, 52428 Jülich, Germany

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ABSTRACT

Effective governance of energy system transformation away from fossil resources requires a quantitative understanding of the diffusion of green technologies and its key influencing factors. In this article, we propose a novel machine learning approach to diffusion research focusing on actual decisions and spatial aspects complementing research on intentions and temporal dynamics. We develop machine learning models that predict regional differences in the accumulated peak power of household-scale photovoltaic systems and the share of battery electric vehicles from a large set of demographic, geographic, political, and socio-economic features. Tools from explainable artificial intelligence enable a consistent identification of the key influencing factors and quantify their impact. Focusing on data from German municipal associations, we identify common themes and differences in the adoption of green technologies. Specifically, the adoption of battery electric vehicles is strongly associated with income and election results, while the adoption of photovoltaic systems correlates with the prevalence of large dwellings and levels of global solar radiation.

1. Introduction

The mitigation of climate change requires a rapid transformation of our energy system [1]. Renewable energy sources, especially solar photovoltaics (PV), are abundant and cost competitive [2,3]. Similarly, battery electric vehicles (BEVs) have experienced remarkable advancements over the past decade, characterized by reduced costs, extended range, and increased longevity [4]. However, the transition to sustainable energy and mobility is not just a matter of technology availability and costs [5]. The adoption of renewable power sources or battery electric vehicles usually depends on decisions by public or private investors. Understanding the determinants of these decisions is crucial for grasping the potential for transformation of the energy system.

The diffusion of green technologies shows large regional differences, even within a single country. In Germany, the diffusion of household-size PV systems has progressed fastest in the south and slowest in the northeast as well as some areas in the west (see Fig. 1). The diffusion of BEVs shows notable differences between western and eastern federal states and some hotspots of rapid adoption (see Fig. 1). These hotspots include municipal associations in the commuter belts of larger cities such as Munich, cities with automobile manufacturers such as Wolfsburg, but also smaller municipal associations. Notably, some neighboring municipal associations reveal strong differences in the level of adoption of PVs or BEVs which cannot be explained by different legal or geographic conditions. What causes these strong regional differences and what can we learn about the drivers and barriers to the adoption of green technologies?

Various studies have examined determinants of PV [8,9] and BEVs adoption [10–12], each providing valuable insights while approaching the subject from different perspectives. Statistical research mostly relies on regression models that analyze a limited set of potential influencing factors. Survey-based studies typically investigate investment intentions and are thus prone to the intention-behavior gap which is a central theme in green consumption [13]. Agent-based models are routinely used in innovation research [14], but are often fitted to simplified socio-economic or spatial data [15,16]. Finally, theoretical work on the

* Corresponding author at: Institute of Climate and Energy Systems: Jülich Systems Analysis (ICE-2), Forschungszentrum Jülich, 52428 Jülich, Germany.
** Corresponding author at: Institute of Climate and Energy Systems: Energy Systems Engineering (ICE-1), Forschungszentrum Jülich, 52428 Jülich, Germany.
E-mail addresses: s.venghaus@fz-juelich.de (S. Venghaus), d.witthaut@fz-juelich.de (D. Witthaut).

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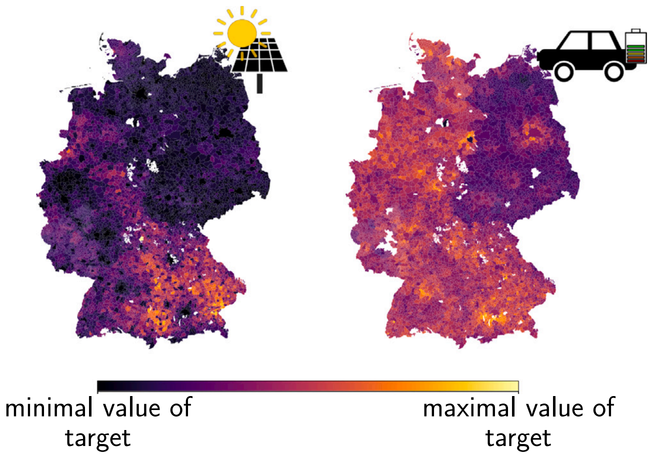

Fig. 1. Regional differences in the adoption of green technologies in Germany. Left: Aggregated peak power of house-hold scale PV systems normalized by the number of households installed until December 31, 2021. Right: Share of battery electric vehicles among all privately owned vehicles as of April 1, 2024. Data has been obtained from Marktstammdatenregister, an open-access registry by the Bundesnetzagentur (Federal Network Agency) [6], and Kraftfahrt-Bundesamt (Federal Motor Transport Authority) [7] and aggregated on the level of municipal associations.

geography of sustainable transitions has also contributed to the field but often neglects differences between technology groups [17]. Overall, these approaches highlight important facets of technology adoption, but a comprehensive data-driven analysis of the regional diffusion of green technologies is lacking.

We address this gap by proposing a different approach to diffusion research based on data-driven analyses relying on eXplainable AI. In contrast to some of the prior research, our analysis focuses on actual decisions and spatial characteristics of the diffusion process. Furthermore, we point out similarities and differences in the adoption of two different technology groups. Most importantly, we avoid a priori assumptions about the putative factors driving the diffusion, but propose to identify these factors directly from large-scale datasets using methods from eXplainable AI (XAI). XAI provides new methods for data analysis and enables new routes to scientific insight [18], with several advantages: First, machine learning (ML) models can describe any nonlinear relationship and feature interaction and thus go well beyond established linear regression models. Second, ML models can handle many possibly correlated input features, so we do not need to impose prior assumptions or manually select features. Finally, XAI provides a method for mathematically consistent model explanation which reveals the contribution of each feature to the model prediction. In contrast to classical sensitivity analysis, this approach avoids the restrictions imposed by the ceteris paribus assumption.

Specifically, we develop two machine learning models that predict the accumulated peak power of household-scale PV systems and the share of BEVs per municipal association from a common set of demographic, geographic, and socio-economic features. We focus on Germany, where PV and BEV adoption started early and high-quality statistical data is available. Using SHapley Additive exPlanations (SHAP) [19], we can identify key influencing factors by systematically comparing the adoption across all municipal associations. Applying the same modeling approach to PV and BEVs reveals which features constitute general drivers of green adoption and which are technology specific. All data is publicly available to guarantee transparency. The source code used in this work is available at Ref. [20] to facilitate a translation to other datasets.

2. Literature review

2.1. The geography of sustainable transitions

Early research in the diffusion of innovations has focused on the temporal aspects of the diffusion process, revealing different phases of the diffusion process over time [21]. More recently, spatial distribution has gained a lot of interest in regional research and economic geography. This strand of research is commonly referred to as the geography of environmental innovation or the geography of sustainable transitions. The early review article [22] identifies five main research themes in the geography of sustainable transitions: regional policies, localized institutions, local natural resources, local industrial specialization and local market formation. Several early studies, including perspectives on the diffusion of solar PV, were summarized in the special issue [23]. A recent review on the spatial conditions that affect environmental innovations is provided in Ref. [24], which distinguishes between actors, institutions and technological elements.

Our article contributes to three topical research directions in the geography of environmental innovations outlined in Ref. [17]. First, a large part of research on environmental innovations treats green technologies as a homogeneous technology group [17]. In this article, we compare two key technologies and demonstrate pronounced differences. Second, there is a strong research tradition on regional supply-side factors that promote environmental innovations [25]. Our article focuses on the demand-side to quantify which factors facilitate the adoption of environmental innovations (cf. Ref. [26]). Finally, there is a need for empirical research on the role of institutional factors as well as societal norms and beliefs [17]. We will partially incorporate norms via local election outcomes. Furthermore, strong differences between model predictions and actual values may point to municipal associations with a particular institutional framework that deserve further study.

2.2. The adoption of household-scale PV systems

A large and growing body of literature has examined exogenous and endogenous factors that drive the adoption of photovoltaic systems and other renewable energy technologies, see [8,9] for recent review articles.

Empirical research typically focuses either on individual households (see, e.g., [27,28]) or on an aggregated level (see, e.g., [29,30]). Peer and neighborhood effects have been studied in [31–33]. While prior works generally rely on the analysis of a few manually pre-selected influencing factors, we compile a large data set and identify the relevant factors from the model. To do so, we utilize state-of-the-art XAI methods instead of established regression models.

For the case of Germany, several articles analyze the dependence of PV adoption on the housing and settlement structure. Previous studies find a strong correlation with the (inverse) housing density [34,35] and the share of (semi-) detached or single-family houses [34,36,37]. Due to their larger roof area and the undivided incentive and decision power to install PV systems, these types of houses are better suited for PV installations than multi-story buildings [31].

Costs and expected revenues play a major role in the decision-making process for or against PV installations as evidenced by surveys [27,38]. Aggregated studies show a strong positive correlation with the estimated return on investment, which depends on both temporal and spatial factors [39]. Other studies report a strong correlation with local solar radiation [34,35], which determines the yield of a PV system. The impact of the socio-economic status has been studied in Refs. [34,35,39] using different proxy variables. A positive correlation with mean income is reported in Refs. [35,39]. Remarkably, Baginski and Weber observe a converse relation, i.e., a negative correlation with mean income [34]. This finding is attributed to the effect of feature correlations, emphasizing the importance of advanced data analysis methods.

2.3. The diffusion of battery electric vehicles

Research on the exogenous and endogenous factors driving the adoption of BEVs has been reviewed in Ref. [10–12,40,41]. Below we summarize results for six categories of importance: policies, personal preferences, perceived properties of BEVs, costs, and socio-economic and demographic factors. We note that most prior studies analyze the effects of a few categories or even the sole effect of a single feature within a category. Overall, the mutual analysis of different categories within one methodological framework is rare.

Many governments have implemented policies that provide financial and non-financial incentives for adopting BEVs. Subsidy programs supporting either BEV purchases or charging infrastructure effectively increased BEV sales, e.g., in Norway [42], the US [43] and Germany [44]. Similarly, carbon taxes leading to higher operating costs for internal combustion vehicles (ICVs) and thus a relative financial benefits of BEVs lead to increasing BEV registrations in Sweden [45].

Personal preferences have an influence on the adoption of BEVs. Both survey and statistical studies found that a high level of technological competence, higher education, and a strong interest in climate change are positively related to BEV adoption [46–49]. Social reinforcement can strongly influence the adoption of BEVs as analyzed in terms of neighborhood effects in Ref. [50]. Notably, peer effects can be quite heterogeneous: Ali et al. found a strong effect for high earners but not middle earners in India [51].

The perceived properties of BEVs in comparison to ICVs strongly affect preferences and decisions. The limited range of early BEVs was an important factor for many potential customers, summarized under the term "range anxiety" [52]. Similarly, several studies find a negative relation between customers' average travel distance and their willingness to purchase a BEV [48,53]. In addition, the longer charging time of a BEV had a negative impact on attitudes towards BEVs [54]. Against this background, several studies have found that the availability of public charging infrastructure is positively related to the adoption of BEVs [48,53–56]. However, the geographic aspects of this relation are complicated, as public chargers are often used by commuters rather than residents [49].

Purchase costs for BEVs are higher than for ICVs, while operating costs are typically lower [57]. Several studies have found that these higher purchase costs have a negative impact on (stated) preferences for BEVs [51,54]. Similarly, the potential cost of battery replacement discourages potential consumers [58]. Given these cost differences, it is not surprising that socio-economic factors have a strong influence on BEV adoption. Several studies report a positive correlation between income and the likelihood of a BEV purchase [47,48,53,59].

Demographic factors, particularly age, gender and household size, strongly affect the adoption of BEVs. Several studies agree on the influence of customers' age [46,55,59,60]. In particular, male consumers up to 45 years are more likely to purchase a BEV [46,54,60], while women are typically underrepresented [46,60]. Households with two vehicles are more likely to own a BEV [49], while opposing results have been obtained for household size [46,60].

Urbanity may affect the diffusion of BEVs, but prior studies do not provide a coherent picture [47,55,60]. The share of commuters crossing municipalities was found to be positively related to BEV adoption [53].

2.4. XAI in energy research

A variety of ML applications have been proposed in energy science, but the vast majority focus on purely technical or economic aspects. For example, ML methods are routinely used in power system planning and operation [61] or electricity price forecasting [62]. Furthermore, most applications are based on black-box models that lack any interpretability, which severely limits scientific insights [18].

Explainable ML is a very recent and rapidly growing research field with various applications in energy research (see [63] for a recent review). However, most applications focus on purely technical or economic applications, while socio-technical aspects have received little attention so far. Most notably, a recent study by Alova et al. used explainable AI to predict and explain the success or failure of power generation projects on the African continent [64]. A recent analysis of energy poverty in the Global South using SHAP was provided in Ref. [65].

3. Methods

3.1. Methods overview

To analyze spatial differences in the adoption of green technologies, we trained two machine learning models to predict (i) the accumulated peak power of all PV systems up to 10 $\mathrm{kW_{peak}}$ normalized by the number of households, and (ii) the share of BEVs among all private vehicles respectively for all municipal associations in Germany (see Fig. 2). The model includes about 200 demographic, geographic, political, and socio-economic features. The data sources are described in Section 3.2 below. We use gradient boosted trees as they combine state-of-the-art performance with the possibility of ex-post explainability [19] (see Section 3.3 for details). To facilitate explainability, we further apply recursive feature elimination, i.e., we recursively remove the least important features while maintaining a high model performance (see Section 3.5 for details). We assess the robustness of the analysis by repeating model training and feature elimination in 10 runs with different random test-train splits.

The trained model corresponds to a nonlinear function $f : \mathcal{X} \to \mathbb{R}$ that maps the input features $x^{(1)}, x^{(2)}, \ldots$ to the respective target for each municipal association. We explain this model to identify important features and quantify dependencies between the features. We use SHapley Additive exPlanations (SHAP), which provide a mathematically consistent method for additive feature attribution [66–68]. SHAP values are defined locally for each data point x, but also provide a global understanding of a model [19]. This approach goes far beyond previous studies employing machine learning to detect PV from satellite imagery [69] or using less sophisticated measures of feature importance to identify correlations between socioeconomic variables and PV diffusion detected by a random forest model [70].

Using SHAP values, we can disentangle each prediction of our models into the contribution of the individual features,

$$f\left(x_n^{(1)}, \ldots, x_n^{(P)}\right) = \phi_0 + \sum_{i=1}^{P} \phi_i\left(x_n; f\right), \tag{1}$$

where $\phi_i(x_n; f)$ is the SHAP value of the ith feature, ϕ_0 is the mean over all data points, and $x_n^{(i)}$ is the value of the ith feature for the nth data point. The global importance of a feature is then quantified by averaging the magnitude of the respective SHAP values over all N data points,

$$FI_i = \frac{1}{N} \sum_{n=1}^{N} |\phi_i\left(x_n; f\right)|. \tag{2}$$

Using this approach, we can quantify whether and how strongly any feature is related to the predicted accumulated peak power of household-scale solar PV and the predicted share of BEVs.

3.2. Spatial granularity and data sources

Regional statistical data in Germany is mostly available at the level of municipal associations. Individual municipalities are less suited for statistical analysis because the average size of a municipality differs strongly between German federal states. Here, we follow the definition of municipal associations of the INKAR database published by the Federal Institute for Research on Building, Urban Affairs and Spatial Development [71]. We discard 210 municipal associations from the set,

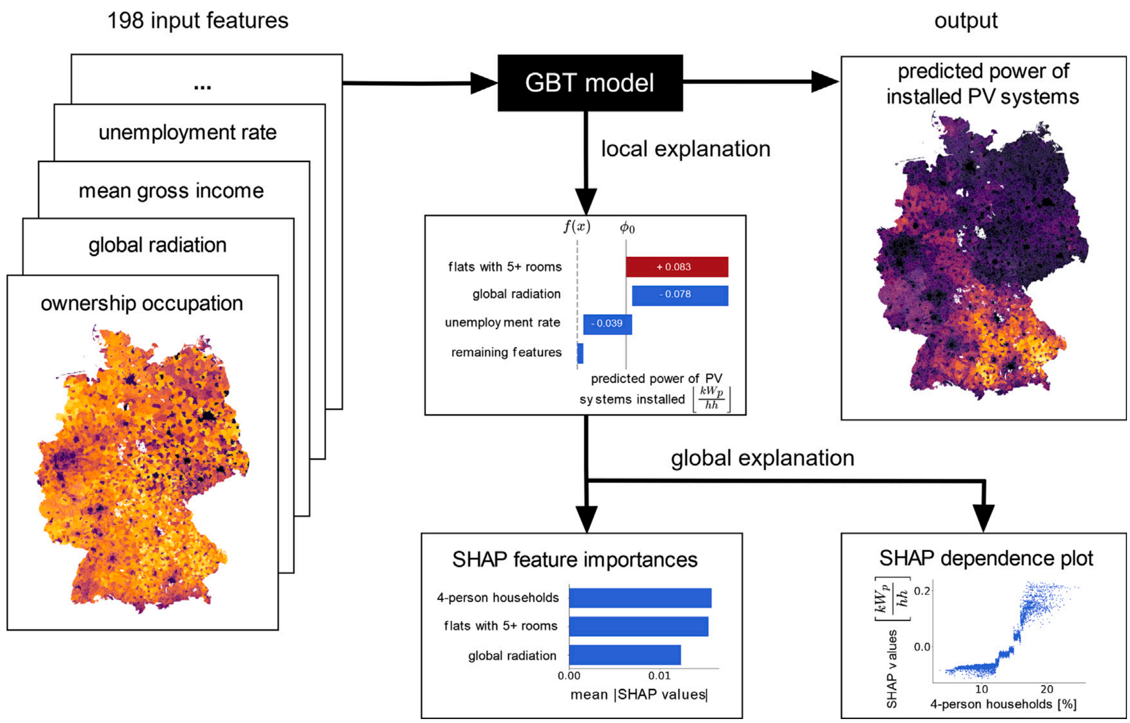

Fig. 2. An eXplainable AI (XAI) model for analyzing the diffusion of green technologies. We train a gradient boosted tree (GBT) model to predict the normalized accumulated peak power of PV systems per municipal association from a large set of socio-economic, demographic, and geographic features. A similar model is trained for the share of BEVs. SHapley Additive exPlanations (SHAP) provide a local explanation for each data point x_n: The model prediction $f(x_n)$ is decomposed into the contributions of the individual features $\phi_i(x_n; f)$ in an additive and mathematically consistent way. Combining all local explanations enables a global understanding of the model [19]: The importance of a feature i is measured by the average magnitude of the SHAP values $|\phi_i(x_n; f)|$. The impact of a feature is quantified in a dependence plot showing $\phi_i(x_n; f)$ versus the feature value x_n^i.

in most cases due to zero population (see supplementary material). We end up with a data set of 4408 municipal associations for the analysis.

Data on solar PV systems was obtained from the Marktstammdatenregister, an open-access registry by the Bundesnetzagentur (Federal Network Agency) [6]. Registration in this database is mandatory for all grid-connected PV systems in Germany. For the overall analysis, we include all entries that (i) were installed in 2021 or earlier, (ii) registered before November 1, 2022, and (iii) had a net nominal power of at most $10\,\mathrm{kW_{peak}}$. Finally, we aggregated the peak power on the level of municipal associations.

Data on the diffusion of BEVs was obtained from the Kraftfahrt-Bundesamt (Federal Motor Transport Authority) [7]. We consider vehicles owned by private persons as of 1st of April 2024 and aggregate the number of vehicles on the level of municipal associations.

We consulted several data sources to create a set of 198 explanatory variables. The INKAR database alone provides 182 of these [71]. These variables cover, among other things, the domains of age, gender, income, housing and settlement structure, the level of urbanity, and construction activity. We further included data from the German 2011 Census on the size of households and the owner-occupation of dwellings [72] and results of the elections for the Bundestag in 2017 published by the Federal Statistical Office and the regional bureaus of statistics [73]. We approximate the average global radiation in municipal associations based on the average global radiation on an optimally inclined surface as available in the SARAH Solar Radiation Data published by the Joint Research Centre of the European Commission [74]. The supplementary information provides further information on the data preprocessing and a complete list of all explanatory variables. Notably, some variables are available only at the county level, so we allocated the same values to all municipal associations in the respective region. In the GBT model for the diffusion of BEVs we also use the aggregated power of household-scale PV systems and the number of public charging stations as explanatory variables.

3.3. Gradient boosted trees

Gradient boosted trees (GBTs) offer a state-of-the-art performance for many machine learning applications [75] and are especially suited for explainable AI approaches [19]. The output of a GBT model is the weighted sum of the predictions of individual decision trees [76]. During training, new trees are added to reduce the prediction error quantified by the L2 loss function. GBTs perform inherent feature selection, which makes them robust to the presence of correlated or irrelevant features. This is essential for the given data set. To fit our GBT model, we used LightGBM, which is a scalable gradient tree boosting implementation that includes several advanced techniques to speed up the training process [77].

The fitted ML model predicts the targets with sufficient accuracy as quantified by the R^2 score, which describes the proportion of variation in the target data that is explained by the model. To facilitate explainability, we further apply recursive feature elimination, i.e., we recursively remove the least important features while maintaining high model performance (see Section 3.5 for details) The model for accumulated PV power shows an R^2 score of slightly below 90% until the number of features falls below 15 (see Fig. 3). We therefore fix the input features to these 15 most important features for the subsequent analysis. The resulting score $R^2 = 88.7\%$ on the test set is very high given the heterogeneity of the data and the socio-economic context. Similarly, the model for the share of BEVs shows a performance of around 80% until the number of feature drops below 15. We thus fix the input features to these 15 most important ones in the following, reaching a score of $R^2 = 79.3\%$. The GBT models significantly outperform a LASSO regression trained for comparative benchmarking purposes for the adoption of PV (see supplementary information).

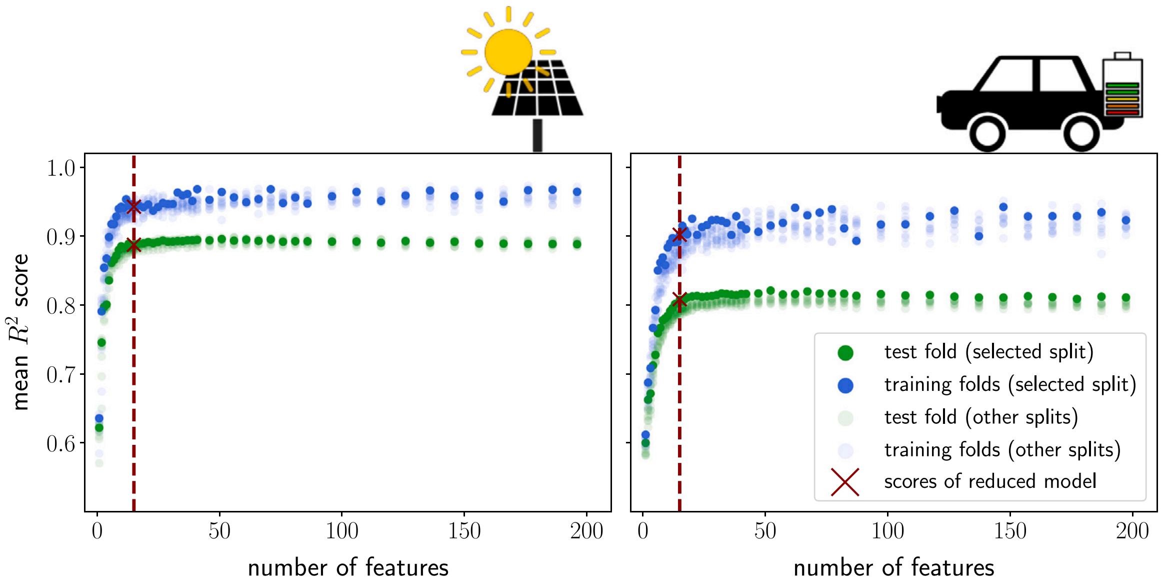

Fig. 3. Performance of the developed GBT models. We apply recursive feature elimination to improve the interpretability of the developed GBT model. The figure shows the model performance quantified by the R^2 score as a function of the number of features for the training folds (blue) and test folds (green) observed during 5-fold cross-validation. Based on these results, we fixed the number of features to 15 as a good compromise between performance and interpretability for further analysis. Different splits of the data into training, validation, and test sets are used to test the robustness of the model. We select the split with the best performing 15-feature model for further analysis (see Section 3 for details).

3.4. SHapley Additive eXplanations (SHAP)

SHapley Additive eXplanations (SHAP) provide a consistent method for the ex-post analysis of a given machine learning model [66]. For each data point x_n, the model outcome $f(x_n)$ is attributed to the individual features in an additive way, cf. Eq. (1). SHAP is based on the concept of Shapley values from cooperative game theory [78]. It has been rigorously established that SHAP values are unique in satisfying three highly desirable axioms [66,68]:

1. Local Accuracy: The feature attributions assigned to all features and the mean over all data points sum up to the output of the function we intend to explain, cf. Eq. (1).
2. Missingness: If a feature i does not contribute to the outcome of the model, the feature attribution vanishes, $\phi_i(x_n; f) = 0$.
3. Consistency: If a model changes so that a feature contribution increases or stays the same, then the attribution should not decrease. More precisely, let S be an arbitrary subset of features and let $\tilde{f}(x_n; S)$ be the model output where the values of all features not in S are replaced by their baseline values. If for two models f and g and all subsets of features S we have

   $$\tilde{f}(x_n; S) - \tilde{f}(x_n; S\backslash i) \geq \tilde{g}(x_n; S) - \tilde{g}(x_n; S\backslash i),$$

   then the attribution of feature i must satisfy

   $$\phi_i(x_n; f) \geq \phi_i(x_n; g).$$

Being the only feature attribution method satisfying these axioms, SHAP values have gained enormous popularity in the field of XAI. In particular, SHAP enables a *global* understanding of the developed model [19] while other feature attribution methods such as LIME focus on individual predictions [79]. We emphasize that both SHAP and LIME explain statistical relations learned by the model and cannot by themselves identify causal effects.

The definition of SHAP values holds for arbitrary ML models, but the direct application is computationally prohibitive. Tree algorithms allow for several simplifications that enable an efficient computation [19,67]. Hence, we use gradient boosted trees as machine learning models in the current article. We then apply the SHAP package by Lundberg to compute SHAP values, feature importances, and SHAP interaction values [80].

3.5. Model training and recursive feature elimination

For model training and hyperparameter optimization, we randomly divide the dataset into training, validation, and test sets. We perform 10 runs of training and feature elimination with different random splits to assess the robustness of the results. The modeling pipeline was implemented in Python using the package scikit-learn [81].

We apply recursive feature elimination to the GBT models to improve the explainability of the models. To this end, we iterate over the following steps:

(i) For a given set of features S, we train models for 50 random sets of hyperparameters. We use early stopping on the validation set to determine the number of trees in the ensemble and random search via 5-fold cross-validation on the training set for all other hyperparameters.

(ii) Determine the best-performing model for the feature set S, i.e., the model demonstrating the highest mean R^2 score on the respective test sets during cross-validation.

(iii) Compute the SHAP feature importances of the best-performing model on the validation set.

(iv) Eliminate the l features with the smallest SHAP feature importances from the feature set S. We start with $l = 10$ and then use $l = 1$ for lower feature numbers.

A detailed analysis of SHAP dependence and interaction was provided for one selected split where the performance, as quantified by the R^2 score, was highest for a fixed number of 15 features. A more extensive description of the machine learning pipeline is given in the supplementary information.

4. Results and discussion

4.1. Influencing factors and dependencies of PV adoption

We first consider the model for the accumulated peak power of PV systems per household (i.e., in units of kWp/hh). We find that seven classes of features are robustly used in all runs and yield the highest feature importances (see left panel of Fig. 4):

1. Three of the four most important features describe the housing situation, i.e., the share of 4- and 5-person households and the number of large flats.

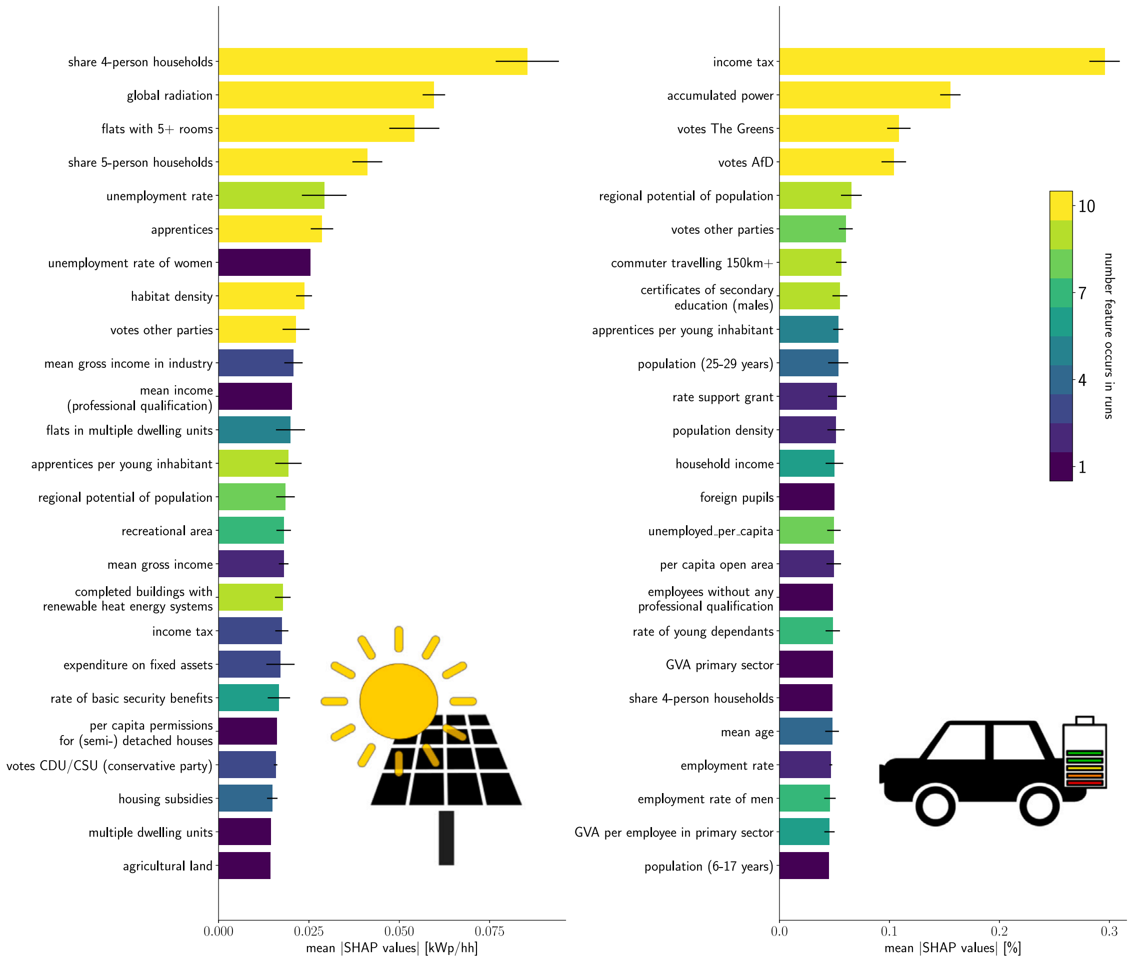

Fig. 4. Key factors influencing the diffusion of green technologies. The bars blot show the SHAP feature importances (2) after feature elimination in the GBT models for the diffusion of household-scale PV systems (left) and BEVs (right). To test the models' robustness, we evaluate 10 runs with different test-train splits and calculate the mean. The color code indicates the number of runs in which the feature is kept after recursive feature elimination, and the error bars indicate the standard deviation. Several important features in the PV model quantify the housing situation, which relates to the rooftop area eligible for household-scale PV systems and the owner-occupation.

2. The second most important feature is the global radiation relating to the economic viability of a PV system.
3. In every run, the model chooses the unemployment rate, either in total or among women.
4. The number of apprentices or the share of apprentices per young inhabitant is chosen in every model run.
5. The model selects 2–3 features related to the degree of urbanity (habitat density, recreational area, and regional population potential).
6. In every but one run, the model selects one feature relating to income, either the mean gross income (in industry), income tax, or median income (professional qualification).
7. The model chooses the number of completed buildings with renewable heat energy systems in nine out of ten runs.

We conclude that the overall findings are highly consistent across different runs, while the model frequently changes between strongly correlated features of a very similar socioeconomic type.

Dependence plots provide a detailed picture of how the key influencing factors relate to the model target – the normalized accumulated peak power of household-scale PV (see Fig. 5). Here, the SHAP value $\phi_i(x_n; f)$ of a feature i is plotted against the value of the respective feature $x_n^{(i)}$ for all data points. We focus on the four most important features for one selected run here and provide the remaining plots in the supplementary information.

Three features relate to the housing and settlement structure: the shares of 4-person households, 5-person households, and flats with 5+ rooms. In all cases, we observe a nonlinear positive correlation. The dependence plots reveal a sigmoid-like relationship of the shares of 4- and 5-person households and the level of PV adoption. We further observe a superlinear relation for the share of flats with 5+ rooms. All three features indicate the share of (semi-) detached houses, which provide the rooftop area eligible for household-scale PV systems. Previous studies consistently reported a positive correlation [34,35,37]. However, these studies were limited to linear correlation and regression models and thus did not uncover the nonlinearity.

Other socio-economic reasons may contribute to the observed dependence. First, high owner-occupation of (semi-) detached houses comes along with undivided decision power to install PV systems [34], and thus undivided financial incentive [82]. Second, 4- and 5-person households are often owned by (young) families with persistence of residence and thus a willingness for long-term investments [36].

Solar radiation determines the revenue of a PV system and constitutes the second key influencing factor of PV adoption. Accordingly, the dependence plot shows a positive relation. We provide a more detailed analysis in the discussion of feature interactions below. The importance of expected revenues in the decision-making process for or against PV installations has been previously evidenced by surveys [27,38]. Consistent results have been obtained in linear statistical analyses in Refs. [34,35,39].

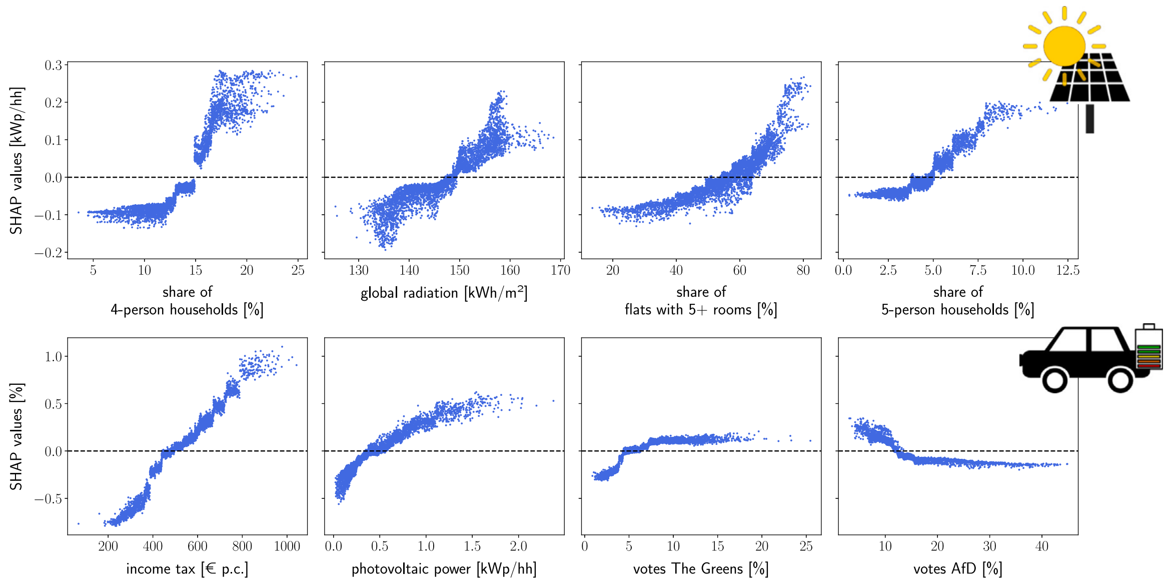

Fig. 5. SHAP dependence plots for the GBT models for the adoption of household-scale PV systems and battery-electric vehicles in the top and bottom row, respectively. The plots show the SHAP value $\phi_i(x_n; f)$ of a feature i against the value of the respective feature $x_n^{(i)}$, where every dot corresponds to one data point n. We focus our analysis on the four most important features from one model run, with features ordered according to their overall importance across all runs. We provide further results on all 15 features in the supplementary information.

Moreover, the SHAP analysis reveals a strongly nonlinear negative relation to the unemployment rate and a positive relation to the mean gross income (see supplementary information). Both features describe the average socio-economic status in a municipal association. The higher the income and the lower the unemployment rate, the more individuals have the financial means to invest in a PV system. Previous studies confirm a positive correlation with mean income [35,39] and a negative correlation with the share of welfare recipients and the unemployment rate [34,39]. Yet, given their research design, they did not find nonlinear relationships. Remarkably, Baginski and Weber [34] observe a converse negative relation with mean income. This finding is attributed to the effect of feature correlations, emphasizing the importance of advanced data analysis methods.

Surprisingly, the SHAP analysis reveals a strong, positive relation between the PV adoption and the number of apprentices employed in a municipal association. This finding has not been discussed in the literature and may be attributed to different reasons. The number of apprentices may provide an indicator of the general level of education, the overall economic activity, or the number of craftsmen and specialized enterprises offering technical services. This finding highlights the need for further investigation beyond the scope of the given data.

Finally, the accumulated peak power of PV is negatively correlated with habitat density and recreational area. The relationship with recreational area is strongly nonlinear. Both features provide a proxy for the urbanity of municipal associations. Urban, densely populated areas provide less rooftop area for PV systems per person. Prior research led to contrasting results on this topic [34,35].

4.2. Influencing factors and dependencies of BEV adoption

We now turn to the second model, which predicts the share of BEVs. The SHAP analysis reveals that the key influencing features are surprisingly different to PV adoption despite being derived from the same dataset (see right panel of Fig. 4). Four features are robustly chosen in every model run and show the highest average feature importances: the income tax per capita, the accumulated peak power of household scale PV systems, and the share of votes for the Green Party and the far-right party AfD in the last federal election. In addition, the regional potential of the population, the share of commuters traveling more than 150 km to work, the share of certificates of secondary education and the votes for other, smaller parties are chosen in most model runs.

For a more detailed analysis, we turn to dependence plots, again focusing on a single run and the most important features. Per capita income tax is the most important one. It has an almost linear relation to the share of BEVs, reflecting that the higher the average income, the more individuals have the financial means to purchase a BEV. The positive role of income has previously been shown both for stated preferences [46,48] and actual decisions [47,53,59].

The accumulated peak power of household scale PV systems ranks second in the selected run and on average. We find a positive relation that saturates for larger feature values. This finding could be related to the strong synergy effects between PV and BEVs, as electricity from the PV system can be used to charge the BEV, reducing the operating costs [46,49].

Remarkably, election results play a strong role in the model for BEV adoption. The reduced model includes the share of votes for the Green party, the far-right AfD, and other parties. The positive relation with the votes for the Green party is not surprising, as environmental awareness is an important factor in the decision for a BEV [46,48,49]. The share of votes for the AfD exhibits a strongly nonlinear relationship with a threshold effect at about 12.4% of votes. Above this threshold, all SHAP values are constantly negative. This reflects the importance of political attitudes: The far-right AfD publicly doubts anthropogenic climate change and repeatedly published statements that show their distrust of electric mobility [83]. However, a further mechanism is possible. The AfD is particularly strong in Eastern Germany such that the model may use the vote share as a geographical proxy variable. A negative relation is also found for the votes for other parties, including in particular the “Freie Wähler”. This party does not generally reject BEVs but has repeatedly opposed plans to ban internal combustion vehicles. The negative relation could either again reflect political attitudes or a geographical effect, as “Freie Wähler” is especially strong in Bavaria.

The share of long-distance commuters is positively related to the share of BEVs, with exceptions for very high values of the feature (see supplementary information). Commuters are an important group of potential customers [53], as BEVs typically have higher purchase costs but lower running costs.

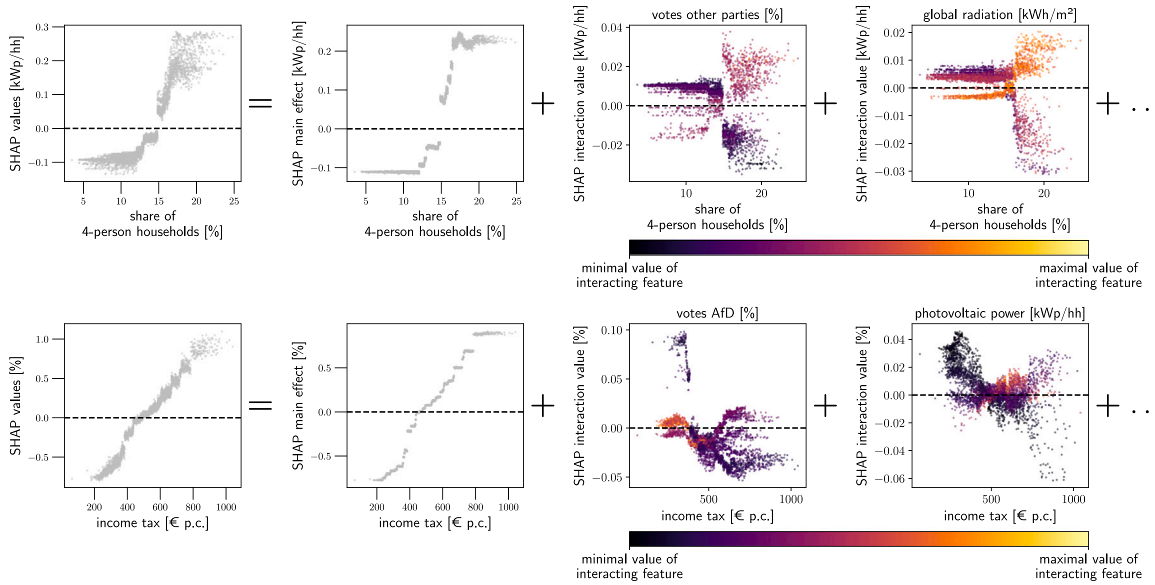

Fig. 6. Disentangling main effects and feature interactions in the SHAP framework. The SHAP value ϕ_i of a feature i can be decomposed into the main effect Φ_{ii} and the interactions Φ_{ij} with other features $j \neq i$, see Eq. (3). Upper row: Interaction in the PV adoption model for the most important feature i = "share of 4-person households". We choose the features j = "votes other parties" and "global radiation" as interacting features, which are among the features with the highest interaction values. Bottom row: Interaction in the BEV adoption model for the most important feature i = "income tax". The strongest interactions are observed for the features j = "votes AfD" and "photovoltaic power". The remaining interactions are omitted for brevity.

The model chooses three demographic features due to their importances. A positive relation is observed for the rate of young dependants, indicating the number of (larger) families in a municipal association. It seems plausible that families are more likely to own two vehicles and thus more likely to purchase a BEV [49]. Furthermore, we find a positive correlation with the regional potential of population in most models. This feature measures the population living within a distance of 100 km. It is high in urban as well as suburban regions, where many families and commuters live. The share of (male) inhabitants with certificates for secondary education shows a strongly nonlinear dependence. Prior research showed that higher education positively affects BEV adoption [46–49].

4.3. Feature interactions

The SHAP framework can be readily extended beyond the impact of a single feature. The SHAP interaction values Φ_{ij} quantify the interactions between two features i and j learned by the model [68]. More precisely, the SHAP value ϕ_i of a feature i can be decomposed into the main effect Φ_{ii} and its interactions Φ_{ij} with other variables $j \neq i$,

$$\phi_i(x_n; f) = \Phi_{ii}(x_n; f) + \sum_{j \neq i} \Phi_{ij}(x_n; f). \tag{3}$$

In analogy to the SHAP feature importances, we can identify the most important interaction effects by averaging the magnitude $|\Phi_{ij}|$ over all data points. In the following, we restrict ourselves to the most important feature and selected interactions. For a comprehensive overview, see the supplementary information.

In the PV adoption model, we focus on the feature i = "share of 4-person households". The SHAP value ϕ_i increases nonlinearly with the feature value $x^{(i)}$. However, the dependence plot displays a strong vertical dispersion, i.e., a strong scattering of the SHAP values ϕ_i for a given feature value $x^{(i)}$. This dispersion reflects the fact that the SHAP value is not only determined by the feature value itself, but also depends on other features, as quantified by the SHAP feature interactions Φ_{ij}, $j \neq i$. Indeed, the SHAP main effect Φ_{ii} shows a superlinear increase with almost no dispersion (see Fig. 6).

Strong interactions are found with j = "votes other parties" and j = "global radiation". In both cases, we find that the increase of the SHAP value with $x^{(i)}$ is amplified in municipal associations with a high value of the interacting features $x^{(j)}$, and attenuated for low values of $x^{(j)}$. That is, the positive effects of the three features do not simply add up, but mutually reinforce each other.

In the BEV adoption model, we observe the strongest feature interactions between income tax and vote share for AfD, followed by the total photovoltaic power (see Fig. 6). In the first case, we observe the strongest interaction effects in municipal associations with small "income tax", where the SHAP main effect shows a steep drop. This drop is mostly suppressed if the vote share for the AfD is low, but persists otherwise. That is, we find a set of municipal associations with low income and strong support for the far-right where BEV adoption drops sharply. In the second case, we find that a weak PV adoption attenuates the increase in BEV adoption with income tax. That is, two mitigating factors of BEV adoption mutually reinforce each other.

4.4. Dynamics of diffusion and influencing factors

The diffusion of green innovations is a highly dynamic process with potential differences in the characteristics of early and late adopters [21,38]. Hence, we expect that feature importances and dependencies may change strongly over time. We focus our analysis of temporal aspects on household-scale PV where sufficient data is available.

The diffusion of household-scale PV in Germany can be divided into distinct phases (see Fig. 7) determined by changes in the policy framework. For a long period of time, PV systems were not profitable. During this phase, subsidies played an essential role [84]. We identify four major changes in the regulatory framework:

1991: The "Stromeinspeisegesetz" [Electricity Feed-In Law] (replaced by the "Erneuerbare Energien-Gesetz" [Renewable Energy Sources Act], EEG in 2001) provides the legal basis for the installation and refunding of household-scale PV systems.

2009: A revised version of the EEG, including a large number of detailed regulations, came into force on January 1, 2009. Subsequently, feed-in tariffs were continuously reduced based on the amount of newly installed PV capacity.

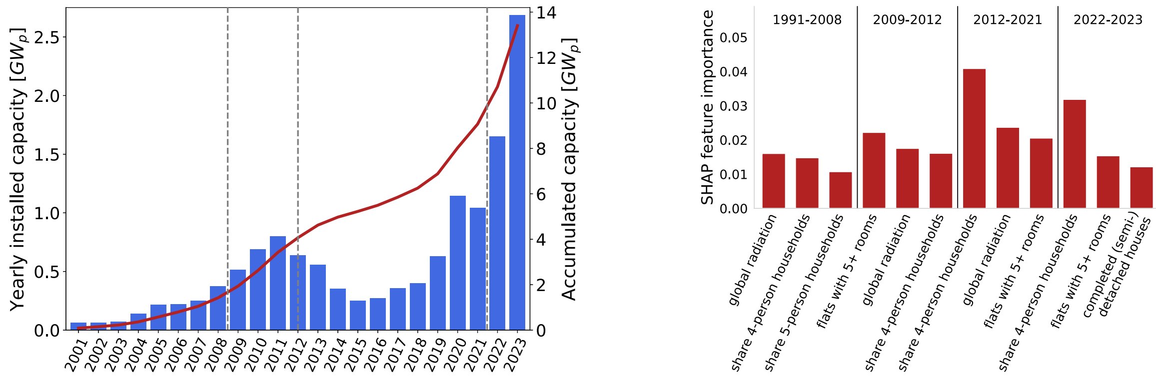

Fig. 7. Key influencing features during different phases of PV diffusion in Germany. Left: Newly built and total accumulated peak power of household-scale PV systems in Germany. We identify four different phases of the diffusion process with strongly differing additions of installed peak power: (i) a slow early stage until 2008, (ii) a first boom after the EEG revision in 2009, (iii) a stagnation phase after the EEG revision in 2012, (iv) the current boom after the most recent EEG revision in 2022. Right: The three most important features and their importances (2) for the four phases of the diffusion process. While solar radiation was most important in the early stages, features related to the housing situation became dominant in later stages. These features relates to the rooftop area eligible for household-scale PV systems and the owner-occupation.

2012: The EEG is revised on July 1, 2012. Feed-in tariffs are substantially reduced. Additional measures are implemented to dampen the deployment of PV.

2022: A new revision of the EEG includes a slight increase of feed-in tariffs. The European energy crisis leads to soaring electricity prices [85].

We analyze how key influencing factors and dependencies change during the diffusion process by training separate ML models to predict the accumulated peak power of the PV systems newly installed in the four phases of the diffusion process. The right panel of Fig. 7 shows how the most important features change.

The most important finding is the declining importance of global radiation. While it is the most important feature in the early phase until 2009, it drops to rank 6 in 2022 and 2023. Household-scale PV systems were much more expensive in the early phase. At that time, a high energy yield was decisive to break even.

After 2022, the two most important features relate to the housing and settlement structure. We conclude that the availability of rooftop area has recently become the decisive influencing factor. The third most important feature is the number of completed (semi-) detached houses. A possible reason for this finding is that, in contrast to earlier periods, new houses are routinely equipped with PV systems. As a result, the number of completed houses gained importance and is now a central driving factor.

4.5. International comparison

The adoption of green technologies can differ strongly between countries due to different framework conditions [8]. Thus, the question arises as to whether our findings can be generalized to other countries. Developing full XAI models for additional countries is beyond the scope of this article as data availability is limited and regional knowledge should complement the analysis. Therefore, we focus on selected results from our prior analysis and provide a comparative study of raw data.

We found that the adoption of BEVs and solar PV differs strongly in terms of the importance of election results, which are interpreted as a proxy for regional differences in norms and values. In Germany, the vote share for the Green Party and the far-right AfD are among the most important features in the BEV adoption model. However, these features are generally eliminated in the PV adoption model. This striking difference is also evident in the raw data (Fig. 8 g,h). There is a strong correlation between the share of BEVs and the Green Party's vote share, with a Kendall rank correlation of $\tau = 0.45$. A much smaller correlation coefficient is observed for the accumulated peak power of household-scale PV. In the context of the XAI model results, we hypothesize that this residual correlation is due to correlated features. This finding is highly relevant to innovation research, as many prior studies have treated green technologies as a homogeneous group [17].

We repeat this analysis for three different countries: Italy, the Netherlands and the United States of America (USA). To this end, we collected data for the results of a recent national elections, the number of BEVs and total vehicles [86–88], the aggregated household-scale peak PV power [89–91] and the total number of households [92,93] in each region. Here, we used data from the 2022 Italian parliament election [94], from the 2023 Dutch election to the house of representatives [95], and the 2024 presidential election in the USA [96]. For Italy and the Netherlands, we use data on the NUTS-2 level, while we use data on the level of federal states for the USA. The spatial resolution for these countries is coarser than that used for Germany due to data availability.

Using this data, we plot the two target features of the XAI analysis, i.e., the aggregated peak power of household-scale PV per household and the share of BEVs, as a function of the share of votes of parties that most likely promotes green technologies given each country's political spectrum (see Fig. 8). Furthermore, we calculate the Kendall rank correlation coefficient to quantify the relation of the two targets to the share of votes.

We find that our main conclusion – namely that support for green parties are more important for BEV adoption than for PV adoption – holds true for all countries under investigation (see Fig. 8). Specifically, we observe that the Kendall rank correlation coefficient is higher for BEV adoption than for PV adoption in all countries. It has to be noted, however, that we consider the share of votes for the Democratic candidate instead of the Green candidate for the USA data because of the two-party nature of the American political system.

However, there are also striking differences to the results for Germany. In the Netherlands, we find a *positive* correlation between the adoption of BEVs and the share of votes for the Green-Left party, but a *negative* correlation for the adoption of household scale PV. Note that large p-values suggest that the null hypothesis cannot be rejected for both household-scale PV in Italy and BEVs in the Netherlands. In the USA, we find a pronounced *positive* correlation for both BEV and PV adoption, but the correlation coefficient is still higher for BEVs. Future research will be needed to conduct a more comprehensive analysis of the transferability of the findings to other countries.

4.6. Contextualizing the results

Effective governance of the transition to sustainable energy requires a better understanding of the adoption of green technologies. Scientific analyses must evolve beyond aggregated optimization models

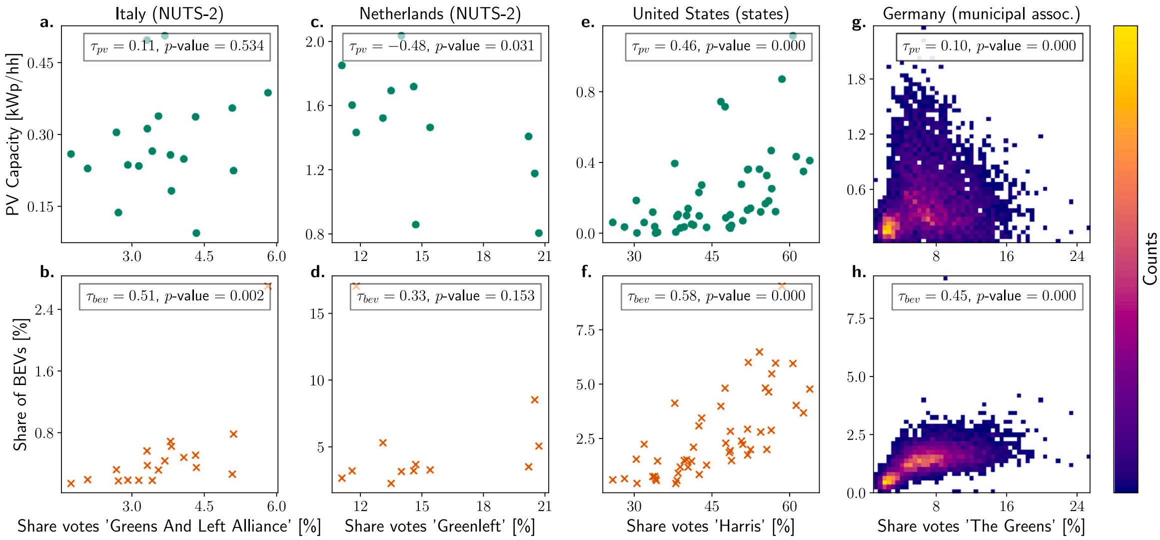

Fig. 8. The relationship between the diffusion of green technologies and election results in different countries. We plot the aggregated peak power of house-hold scale PV systems per household (top row) and share of BEVs (bottom row) in different regions versus the vote share of the Green party in national elections (Netherlands, Italy, Germany) or the Democratic candidate in the presidential election (USA). In the case of Italy and the Netherlands (panels **a-d**), the regions are the NUTS-2 administrative divisions, and for the United States (panels **e** and **f**), we chose federal states. The histogram for Germany in panels **g** and **h** uses the same data as was used for the analysis shown before. The Kendall rank correlation coefficient τ for the respective data set is given in the legend.

to capture political actions and individual motivations, and improve empirical validation [97].

Against this background, we propose explainable Artificial Intelligence (XAI) for empirical research on the diffusion and adoption of green technologies. We have developed a machine learning model that predicts spatial differences in the adoption of household-scale photovoltaic (PV) systems and battery-electric vehicles (BEVs) in Germany at the level of municipal associations. This approach complements current research on the adoption of green technologies in several ways: (i) XAI can readily deal with large heterogeneous data sets and thus mitigates the need for a priori assumptions in empirical studies. SHapley Additive exPlanations (SHAP) identify key influencing factors in the XAI model in a mathematically consistent way. (2) Our focus on actual decisions and spatial differences complements sociological research on intentions and temporal dynamics. (3) The model reveals technology-specific effects that are often neglected in the literature [17].

We find that PV adoption is primarily explained by physical and economic conditions, while BEV adoption is influenced more strongly by income levels, the prevalence of PV systems, and political attitudes. The importance of existing PV systems points to a strong co-diffusion [59] due to synergy effects.

Attitudes and values are known to be important in decisions on green technologies but are notoriously difficult to capture in statistical studies. We tried to capture this aspect by incorporating political preferences via election results on the level of municipal associations. While the Green Party and AfD vote shares are highly relevant in BEV adoption model, they play no significant role in the PV adoption models. We conclude that a differentiated view of green technologies is needed in socio-technical research, cf. the discussion in Ref. [17]. We hypothesize that polarization of opinions and, thus, the importance of individual attitudes may differ strongly for different technologies.

The results thus suggest targeted policy interventions to effectively promote the diffusion of green technologies. Policymakers may consider the socio-economic factors influencing adoption decisions, which vary significantly even within seemingly similar categories of innovations such as green technologies. For rooftop PV systems, policies may target financial incentives that account for structural and geographic differences, particularly in roof area availability and regional solar radiation levels. In contrast, BEV adoption is strongly associated with income and attitudinal factors according to the model. Consequently, policy interventions aimed at improving affordability across income groups alongside educational and communication campaigns to enhance public awareness and understanding of these technologies could be considered. Given the observed co-diffusion of PV and BEVs, joint policy incentives may yield synergistic effects.

Despite these meaningful insights and their potential policy implications, it is important to reiterate that XAI does not provide any causal evidence. The inferred relations could also, for example, reflect reverse causality (e.g., between Green Party election results and renewable technology adoption) or be influenced by confounding variables (e.g., education confounding the effect of income on adoption). To disentangle the relationships identified in this study and assess causality, future research may focus on context-specific econometric analyses employing identification strategies which allow for a causal interpretation. In addition, while our model robustly identifies features with high predictive relevance, it must be considered that some of these features may function as proxies for unobserved or latent factors influencing technology adoption. Political preferences, for example, inferred from election results, do not necessarily reflect individual adoption decisions but may capture broader regional socio-political contexts. Similarly, a feature like the number of apprenticeships may indicate structural characteristics of regional education or economic performance. The occurrence of such proxy features is inherent in the correlational patterns identified and requires a cautious interpretation of the underlying mechanisms. Although the internal validity of the feature selection remains unaffected, further empirical analyses are necessary to examine the actual factors represented by the identified predictors and to better understand their causal relationships. Therefore, combining systematic feature identification through XAI with context-specific empirical validation, involving local expertise, is essential for a more accurate interpretation of the identified predictors.

XAI can promote socio-technological energy research in manifold ways. We envision three ways to generalize the methodology introduced in this article. First, the developed XAI model can be readily adapted to different technologies. Second, the adoption of green technologies can differ strongly between countries [8] due to different policies and a different institutional framework. Comparing XAI models for different countries can reveal differences in the important features and dependencies and thus help to assess national policies and the role of institutions. Investigations should ideally include partners with a local background to facilitate the access to regional statistical data and to enable an informed interpretation of the results, in particular in view of possible causal effects. We provide the source code of our the model under an open license at [20] to foster such investigations. Finally, it would be highly desirable to improve the spatial resolution of empirical models for technology diffusion. Household scale PV systems can be identified from satellite images (see, e.g., [69,70]). XAI models at the household level can quantify the importance of neighborhood effects [33] in comparison to socio-economic factors.

5. Conclusion

This study demonstrates how eXplainable Artificial Intelligence (XAI) can uncover the drivers of green technology adoption using high-resolution spatial data enhancing existing strands of research. By applying machine learning models to the diffusion of household-scale photovoltaic systems and battery electric vehicles in Germany, we identify the key factors associated with actual adoption decisions at the level of municipality associations.

A central finding is that the adoption of PV systems and BEVs is correlated with markedly different factors, despite both being green technologies. PV adoption is primarily shaped by structural geographical and economic conditions, especially the availability of rooftop area and regional solar radiation determining the generated revenues of PV systems. These factors suggest that physical infrastructure and local resource potential remain critical constraints for distributed energy technologies.

In contrast, BEV adoption is influenced more by socio-economic conditions and political attitudes. High income levels emerge as the strongest predictor in our model, followed by existing PV adoption and regional voting patterns. Support for pro-environmental parties correlates positively with BEV adoption, while support for far-right parties correlates negatively, revealing a clear role of attitudes in shaping technology preferences.

Our analysis also highlights how feature importances evolve over time. As PV costs decline, economic viability becomes less dominant, and structural features gain prominence. This shift underscores the need for dynamic policy approaches that adjust to the changing landscape of technology costs and public perception.

More broadly, this work illustrates the potential of explainable AI as a tool for empirical research on innovation and technology diffusion. By identifying relevant influencing factors from large and complex datasets, XAI can reveal differentiated adoption patterns across technologies, regions, and time. This approach opens new pathways for data-driven insights in sustainability transitions, complementing existing theoretical and qualitative research traditions.

CRediT authorship contribution statement

Dorothea Kistinger: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation. **Maurizio Titz:** Software, Methodology. **Philipp C. Böttcher:** Writing – review & editing, Visualization, Validation, Software, Formal analysis, Data curation. **Michael T. Schaub:** Writing – review & editing, Writing – original draft, Supervision, Investigation. **Sandra Venghaus:** Writing – review & editing, Writing – original draft, Supervision, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization. **Dirk Witthaut:** Writing – review & editing, Writing – original draft, Supervision, Project administration, Methodology, Investigation, 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.

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.adapen.2025.100242.

Data availability

All data used in the development of the XAI model are publicly available from their respective sources [6,71–74]. The source code used in this publication is available on github [20].

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