# EVolve

## Predicting Electric Vehicle Adoption

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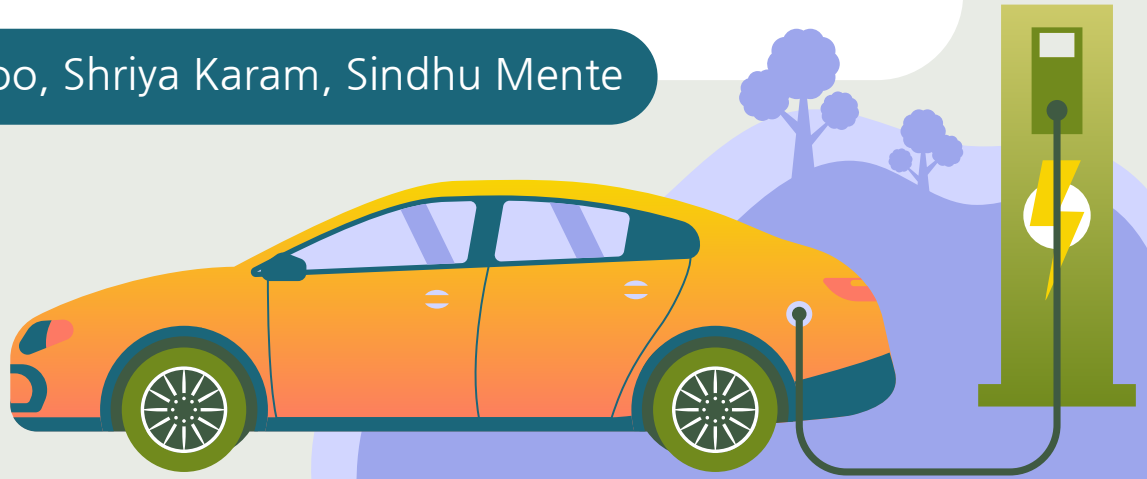
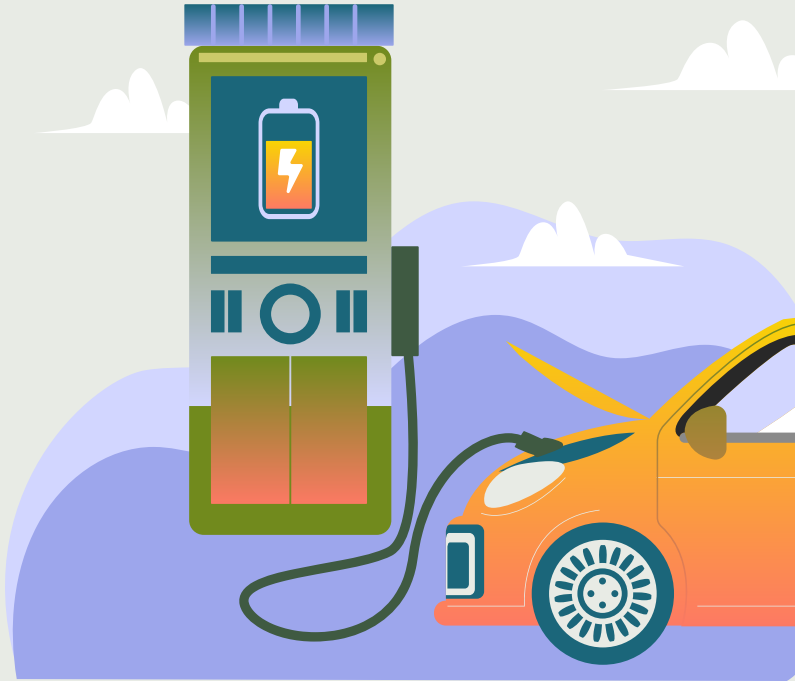


# LESS SMOKE, LESS NOISE

- Transportation is the largest contributing sector to greenhouse gas emissions in the U.S.
- Adverse environmental and health impacts as a result of vehicle emissions
- Decarbonize the transportation industry through electric vehicles



# EV usage is growing, but there are still barriers in widespread adoption.

- Barriers include: charging infrastructure, affordability, and EV performance
- Disproportionately affect certain individuals based on socioeconomic and background factors
- Need targeted efforts to enhance EV usage

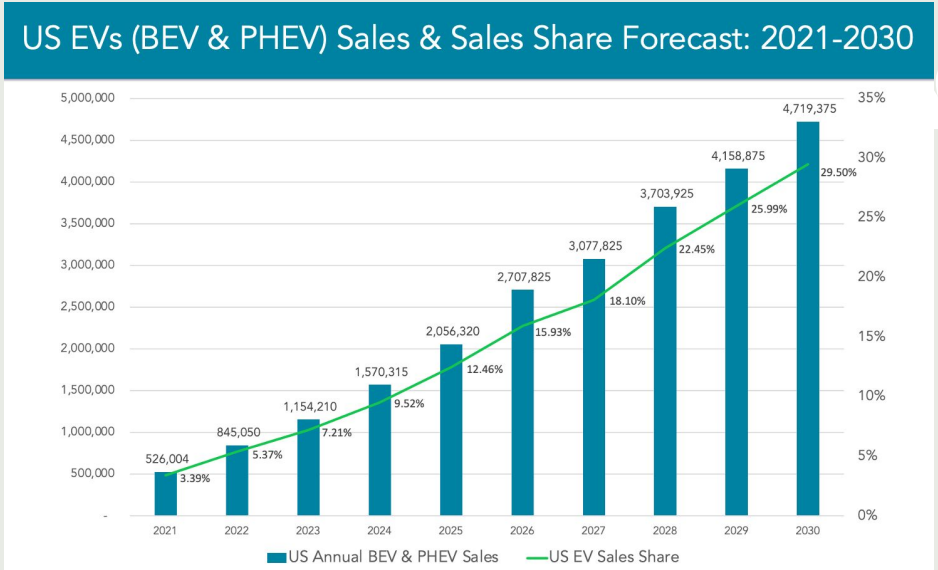



**Figure 1**: US EV sales forecast from 2021- 2030 (source: evadoption).

# Research questions

**Does individual socioeconomic status and prior exposure relate to likelihoods of considering EVs?**

**What targeted recommendations can we provide to policymakers to enhance EV usage?**

# Data description

| Data source | Independent variables | Dependent variable |
| --- | --- | --- |
| **Online questionnaire of residents' attitudes toward zero-emission vehicles (ZEVs)** | **Socioeconomics**: age, gender, education, income, state<br><br>**Household**: electricity usage, home parking, charging<br><br>**Perceptions of EVs**: price, charging, safety, reliability, environmental/health benefits<br><br>**Prior exposure**: EV driving experience, technical interest, familiarity | **Binary variable** denoting whether the individual will/has **adopted (1) or not adopted (0)** an electric vehicle |

# Prior exposure, environmental outcomes, and EV characteristics are related to EV adoption.

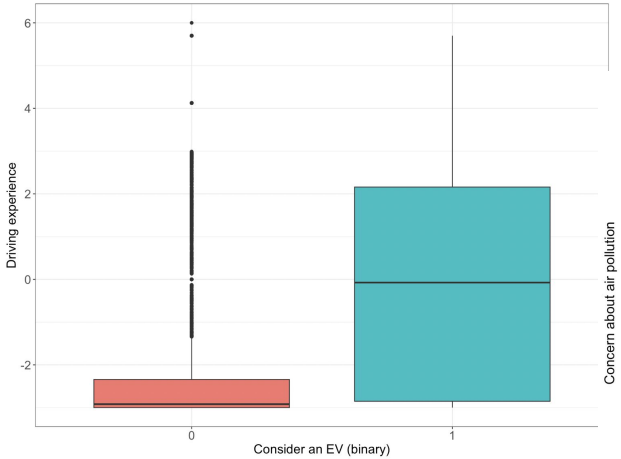



Figure 2

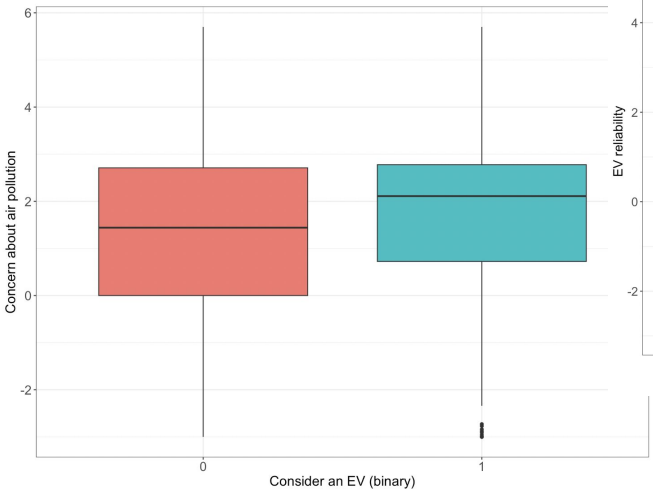



Figure 3

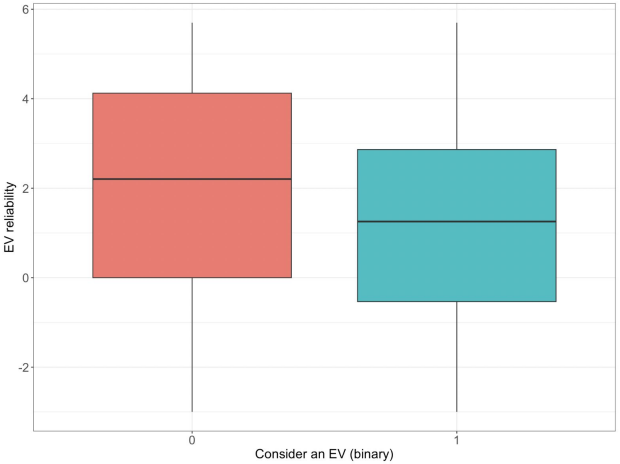



Figure 4

Box plots of not adopting (red) and adopting (blue) electric vehicles by driving experience (**Figure 2**), worry about air pollution (**Figure 3**), and EV vs. gasoline-powered vehicle reliability (**Figure 4**).

# Individuals who have seen more EVSEs in public were more likely to adopt an EV.

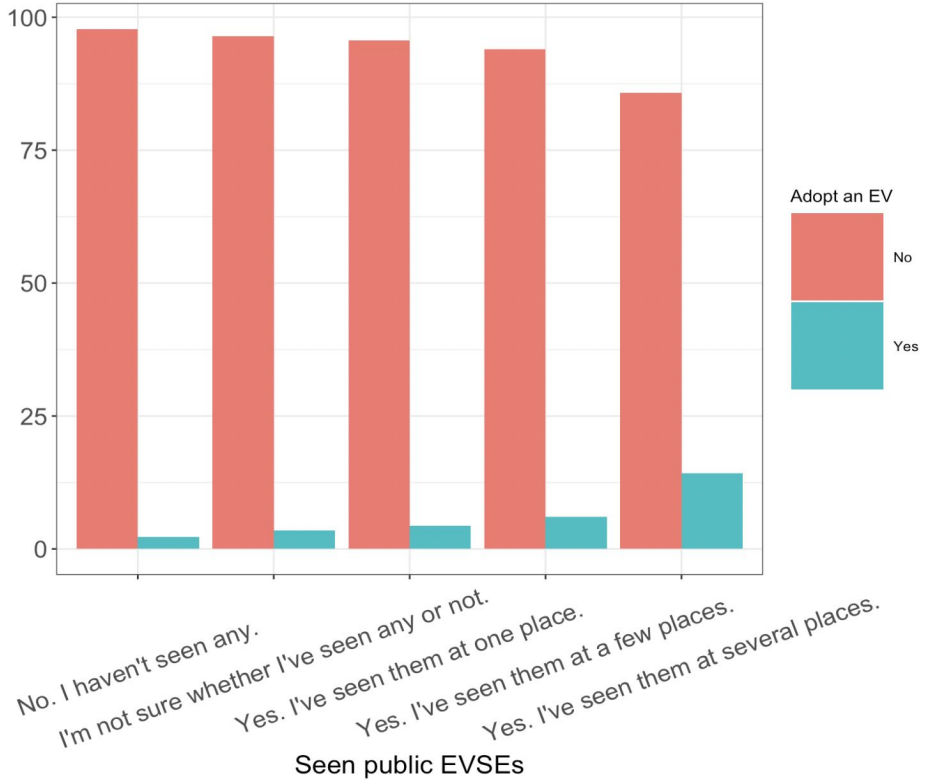



**Figure 6**: Percentage of individuals having seen public EVSEs (i.e. charging stations) to different degrees in either not adopting (red) or adopting (blue) an electric vehicle.

# There is significant variation in EV adoption by education level.

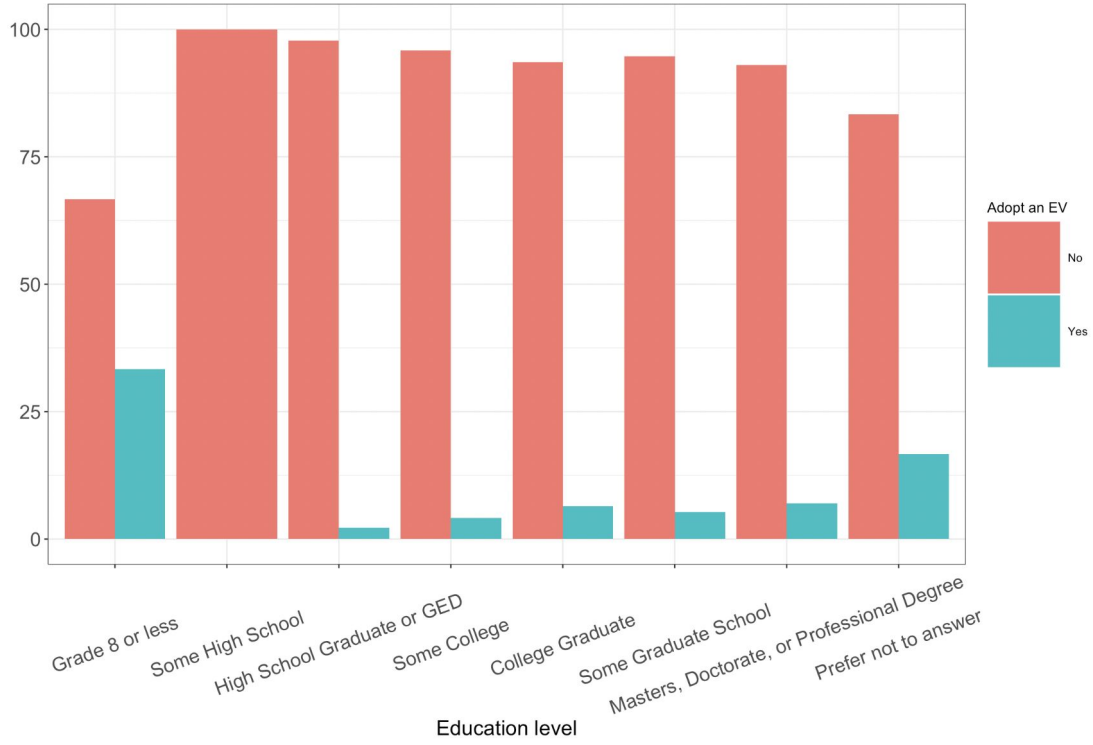



**Figure 5**: Percentage of individuals in each education level either not adopting (red) or adopting (blue) an electric vehicle.

# Proposed methods

## Logistic regression and LASSO

Simple binary model
and feature selection

## Boosting

Adaboost and XGBoost to
improve performance

## Random forests

Ensembling method for
classification decision trees

## Neural networks

More complex parametric
structure for classification

# Class imbalance with initial models

## Distribution of Response Variable

| Will not consider EV (0) | Will consider EV (1) |
|---|---|
| 4954 (~94%) | 294 (~6%) |

- False negatives much more costly than false positives
- Models built on the original dataset rarely identify people actually willing to consider EVs
- Solution: oversample observations in the minority class to increase its proportion

## LASSO Confusion Matrix - Testing Data

| | True 0 | True 1 |
|---|---|---|
| Predicted 0 | 990 | 51 |
| Predicted 1 | 5 | 4 |

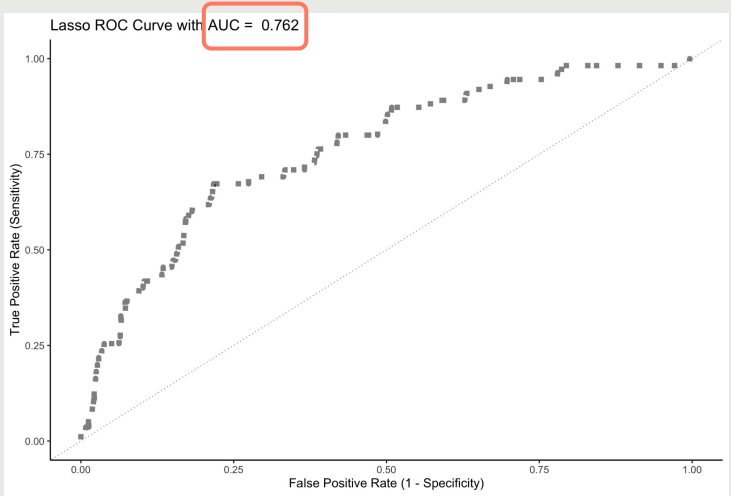
## RF Confusion Matrix - Testing Data

| | True 0 | True 1 |
|---|---|---|
| Predicted 0 | 994 | 54 |
| Predicted 1 | 1 | 1 |

# LASSO (after oversampling)

## Important Variables Identified

- Air pollution/Environmental factors
- Characteristics of EVs
- Demographics of respondent
- **Seeing EVSEs in public - highly significant**




## Important Observations

- Reduced the number of features from 66 to 39
- Identifies over two-thirds of the people willing to consider EVs

### LASSO Confusion Matrix - Testing Data

| | True 0 | True 1 |
|---|---|---|
| Predicted 0 | 763 | 18 |
| Predicted 1 | 232 | 37 |

TPR = 0.672

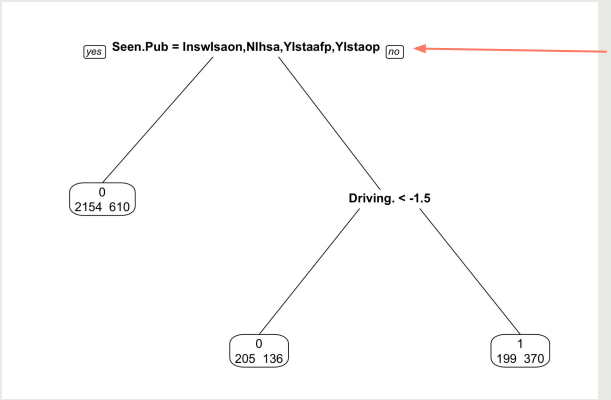
- Far more false positives now
- **Availability of charging stations is not significant at the 0.05 level**

# Tree-based Methods

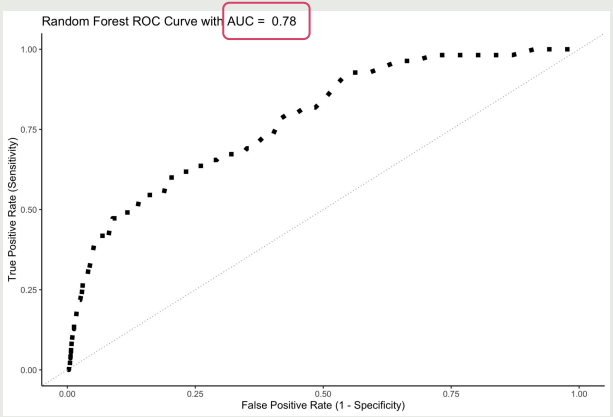
## RF Confusion Matrix - Testing Data

| | True 0 | True 1 |
|---|---|---|
| Predicted 0 | 838 | 25 |
| Predicted 1 | 157 | 30 |

TPR = 0.545




A tree built on the entire dataset splits on the '**Seen EVSEs in public**' variable first




## Important Observations

- RF's AUC is slightly higher than LASSO
- Less interpretable
- **'Seen EVSEs in public' (i.e. charging stations)** reduces deviance the most!

# Summary of results

## Final model: LASSO logistic regression with oversampling.

LASSO has one of the highest AUCs and preserves feature interpretability (compared to all other methods).

## Prior exposure to EVs is a strong indicator of EV adoption.

Individuals who have seen charging stations and had driving experience with EVs were significantly more likely to adopt an EV.

## EV characteristics and demographics are key factors in EV adoption.

Negative perceptions of EV safety and reliability and lower education levels contribute to a lower likelihood of EV adoption.

# Policy recommendations

## Enhance EV charging infrastructure.

Public charging stations contribute to positive perceptions of EVs and greater adoption.

## Promote information on EV usage.

Address the gaps in prior exposure to EVs and enhance public perceptions of EVs.

## Targeted efforts for less educated populations.

Strategically target efforts to encourage more EV usage among less educated populations.

# THANKS!

We are open to any questions and suggestions!