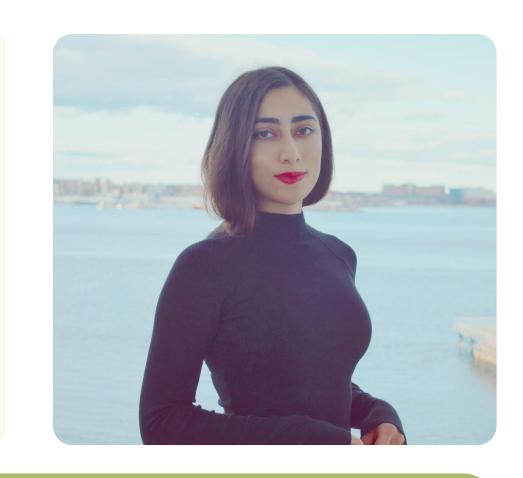
2025 Modeling Mobility Conference Sep 16, 2025, 3:30 – 5:00 PM

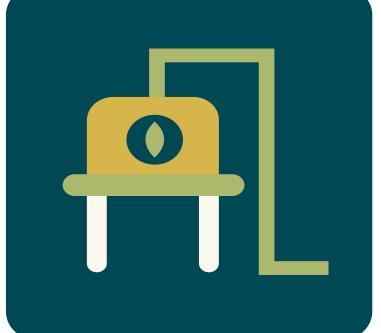
How Can We Spend Electric Vehicle Incentives Smarter?

A Machine Learning Approach to Enhancing Rebate Efficiency in Varied Local Contexts

Helia Mohammadi-Mavi, Dr. Andisheh Ranjbari







Helia Mohammadi Mavi
PhD Candidate
The Pennsylvania State University

momo2025

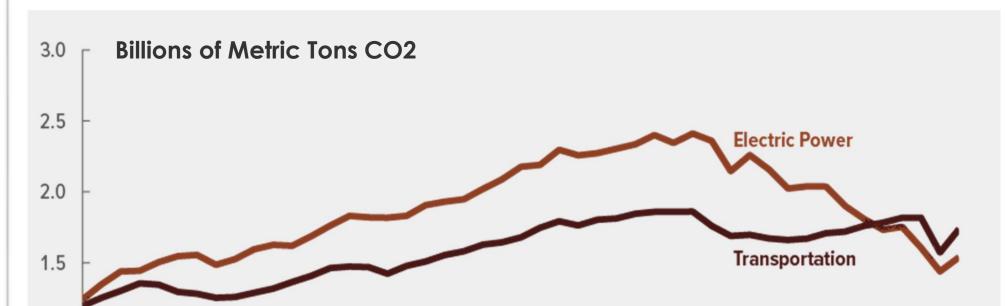




Nearly half of Americans breathing in unsafe levels of air pollutants - report

American Lung Association's study says almoneople live in areas with unhealthy levels of s

The New York Times



1.0

0.5

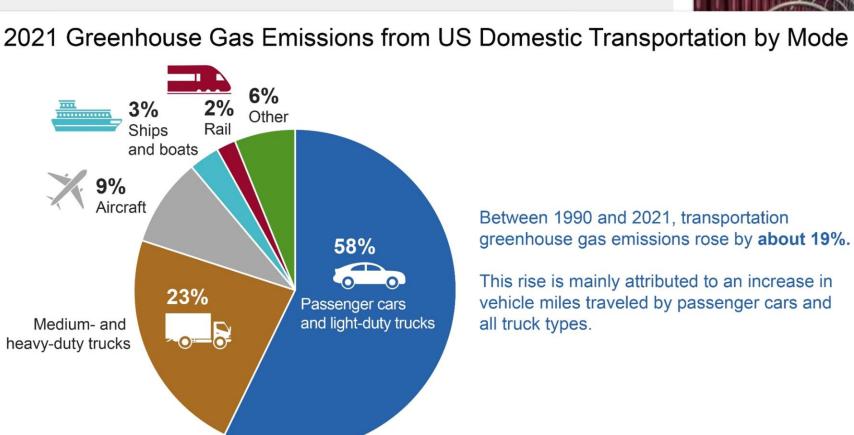
1976

1981

198

S. Greenhouse Gas Emissions unced Back Sharply in 2021

ssions rose 6 percent last year after a record 10 percent ne in 2020, fueled by a rise in coal power and truck traffic as J.S. economy rebounded from the pandemic.



Behavioral Interventions to Promote Clean Transportation

Mode shift

Increasing vehicles' occupancy

Clean vehicle Alternatives

Travel reduction

Route/time optimization

• • •



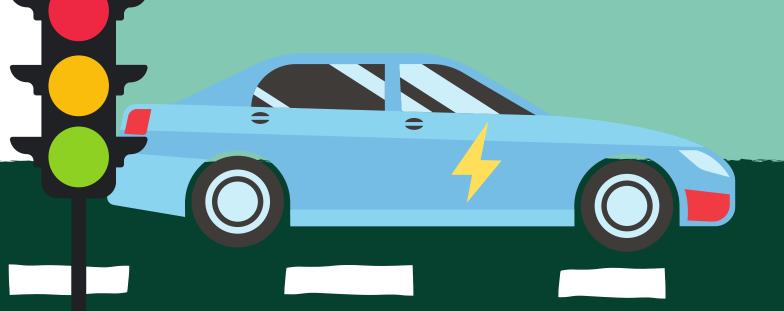




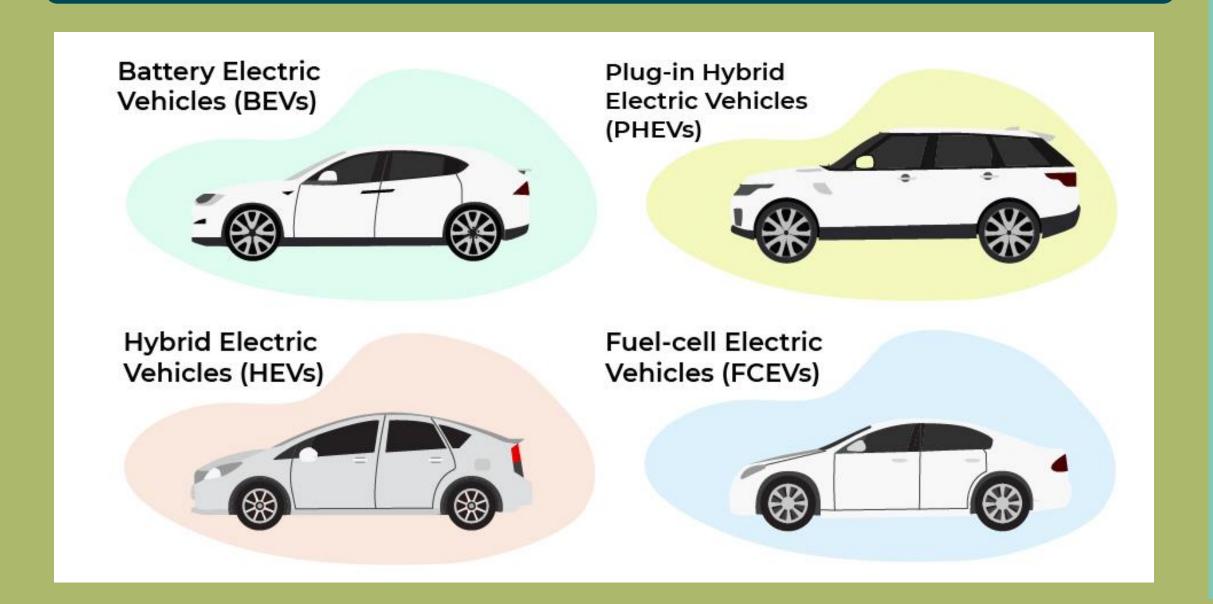


Behavioral Interventions to Promote Clean Transportation

Clean vehicle Alternatives



Problem: Clean Alternatives are Expensive



Credits

Discounts

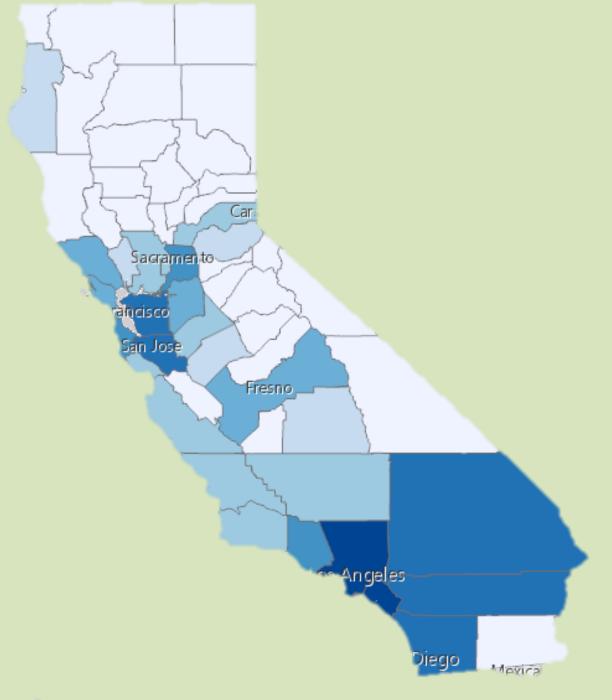
Tax reductions

Rebates









What Types of Data We Used?



Data Sources



Issued Rebates for BEV and PHEV 2012 – 2023 From:

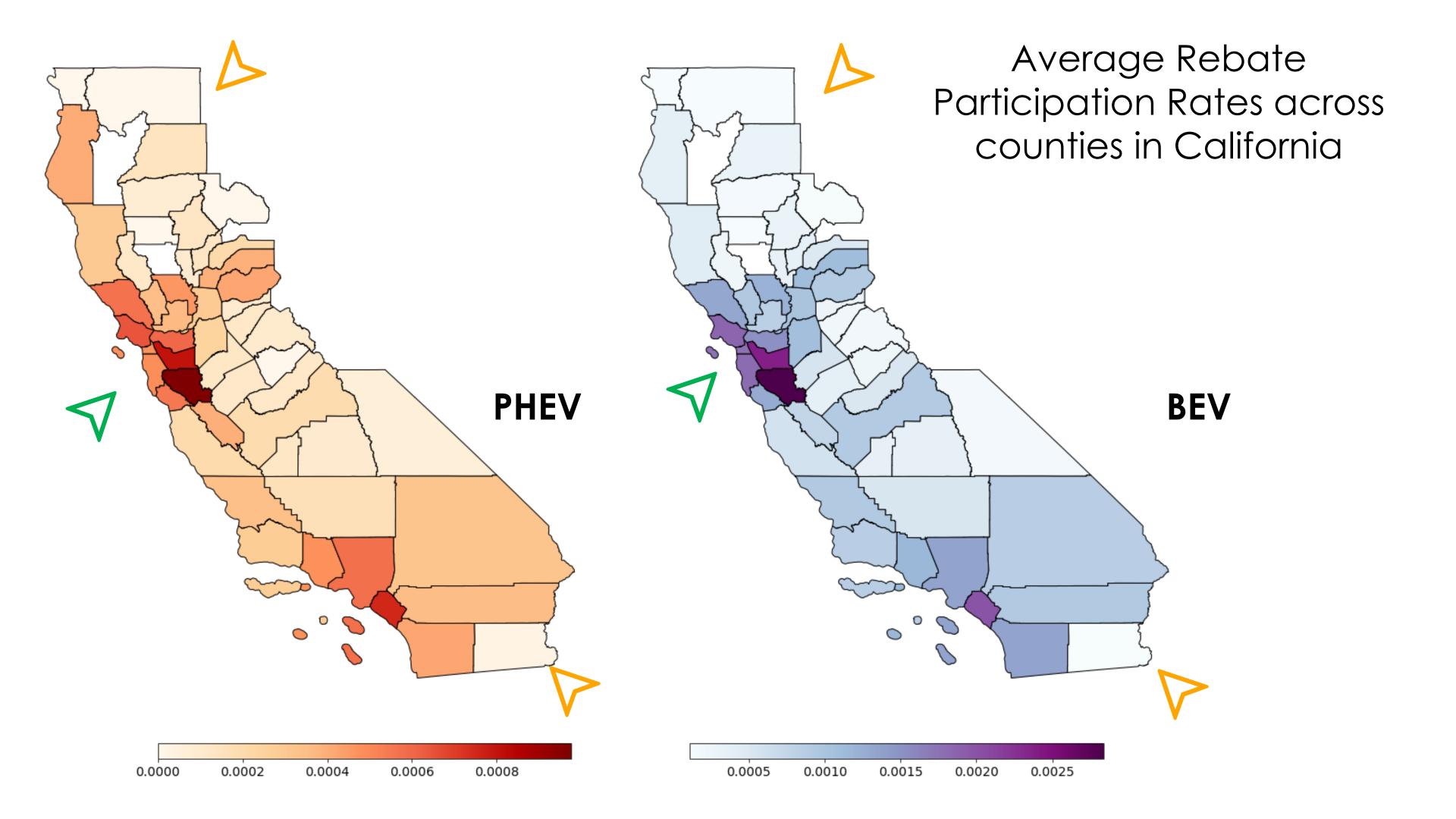


Rebate
Participation
Rate

Aggregated for each county in each year



Total registered vehicles



Data Sources



Age, Gender, Education, Race and ethnicity, Nationality, Household structure, Language



% of Urban and Built-Up, Farmland, Agricultural, Water



Gross Domestic Product (GDP), Income, Labor Force Participation, Employment rate

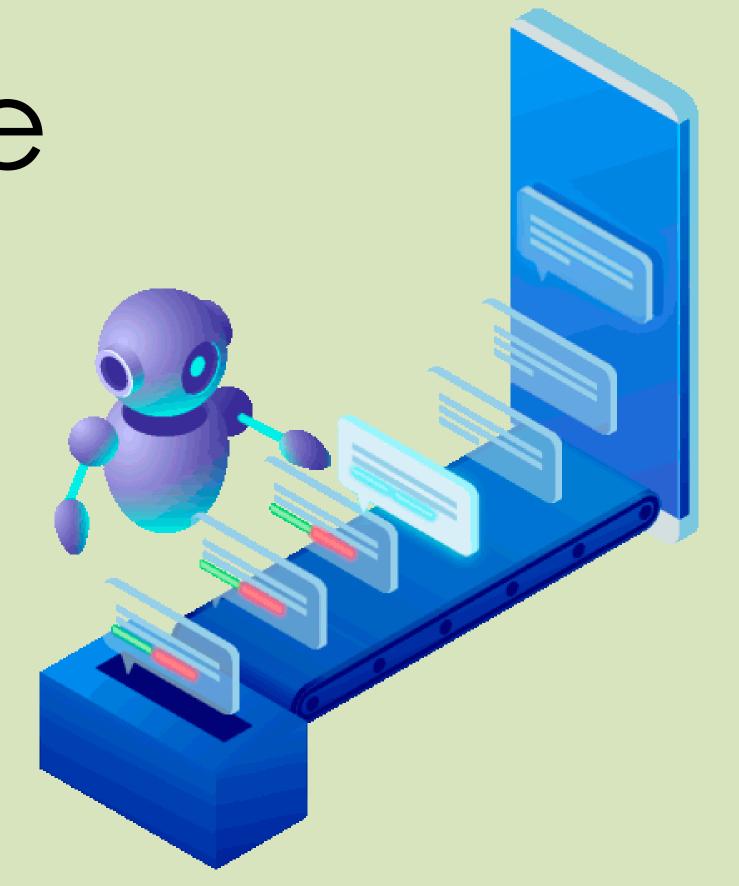


Public transit service and operation



Number of EV charging stations

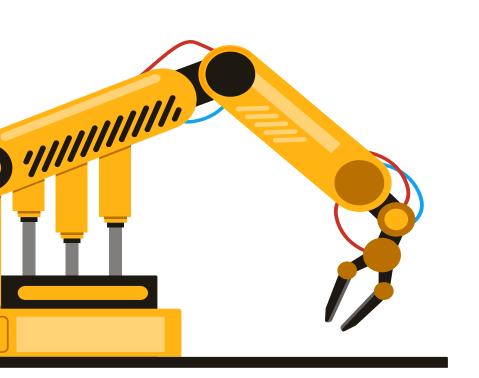
What Was the Analysis
Approach?





Phase One

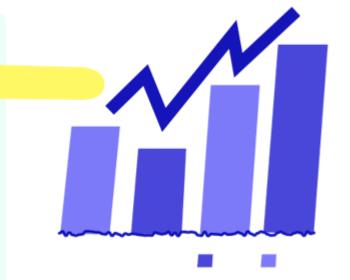
To understand rebate participation patterns in different context and locations



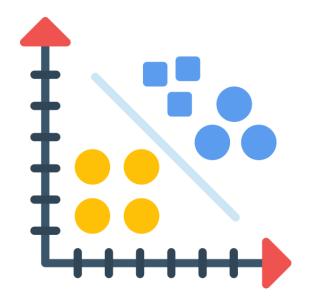


Phase One

Applied Dynamic Time Warping (DTW)
 to capture temporal patterns in
 rebate participation.



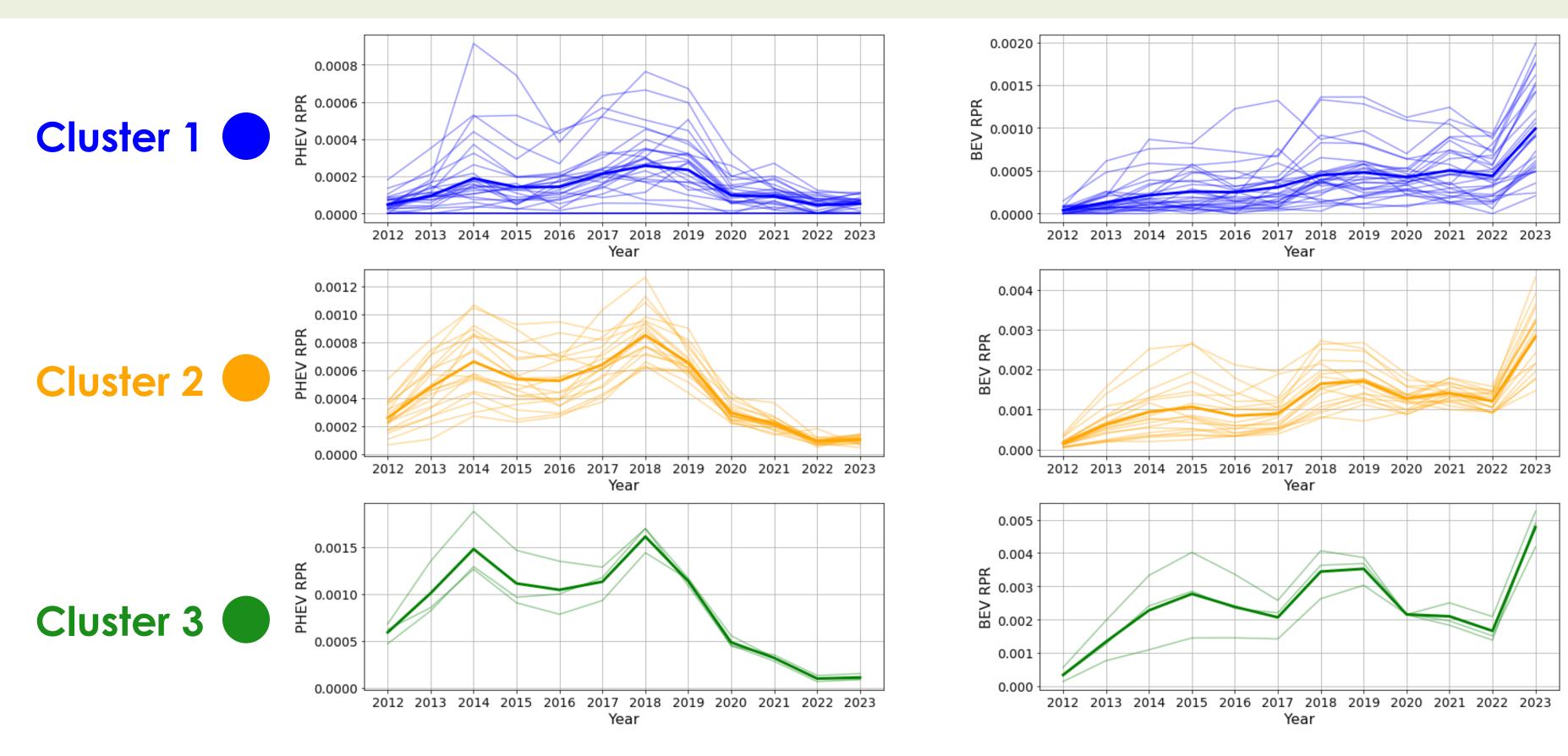
 Grouped counties using K-Means clustering, an unsupervised learning method to identify adoption trajectories.





What did we find?

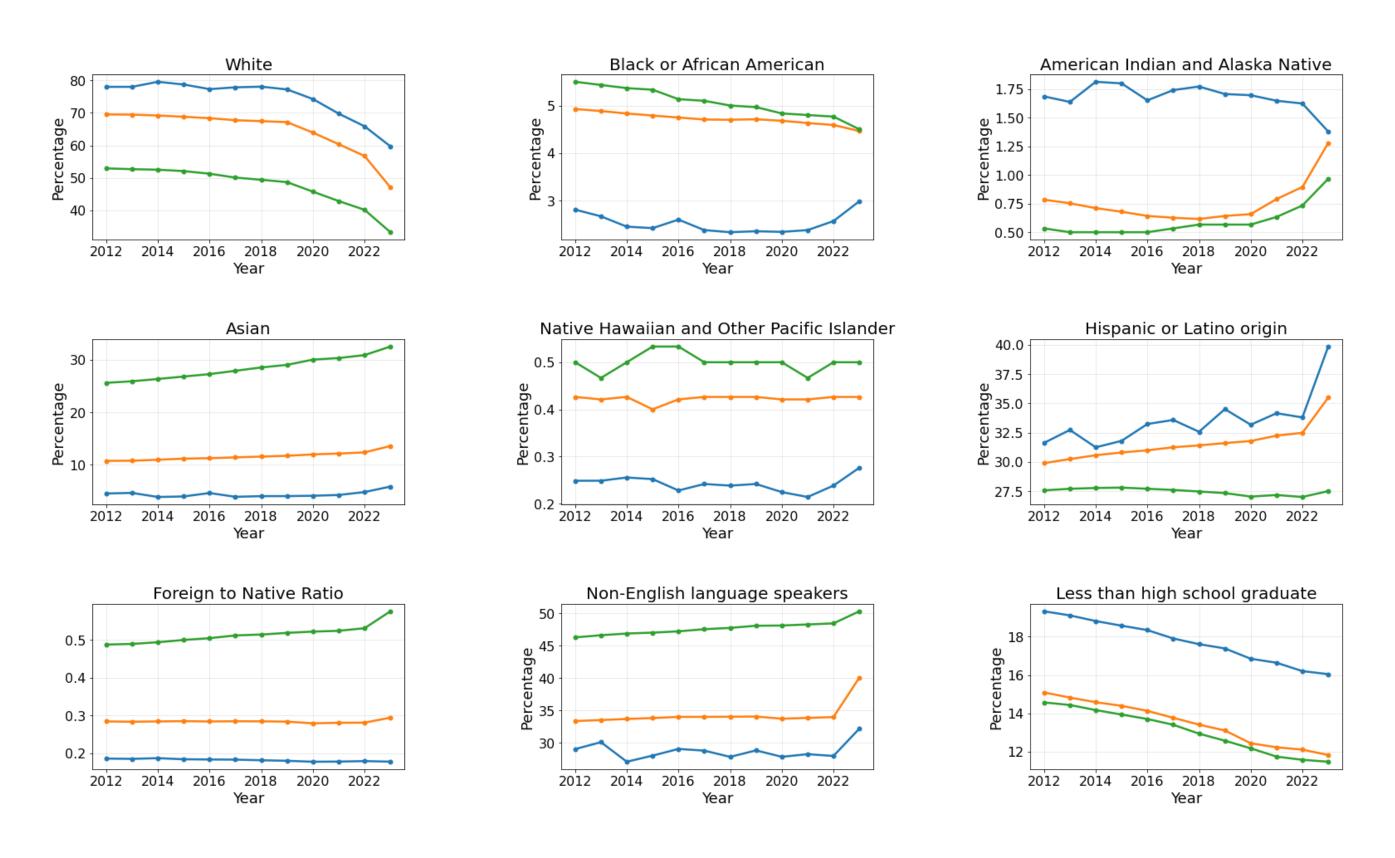
Yearly Average Rebate Participation Rates



PHEV

BEV

Demographic Factors





Demographic Factors

Cluster 1

- Less diversity
- Older population
- lower educated people

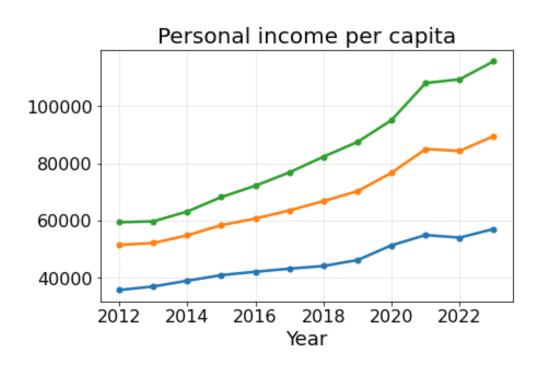
Cluster 2

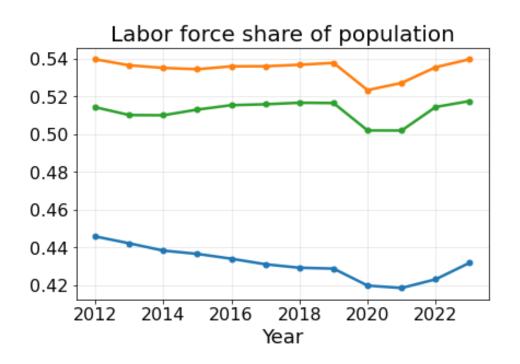
In between

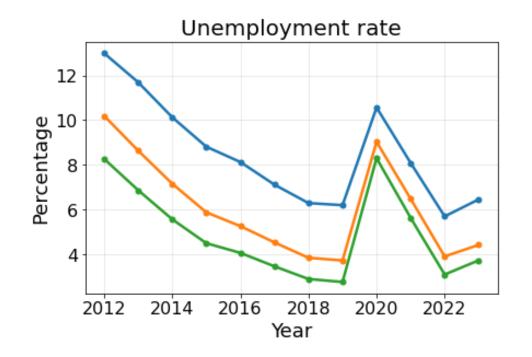
Cluster 3

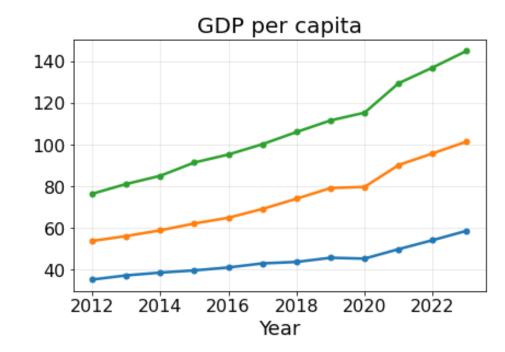
- High diversity
- Younger population
- Higher educated people

Economic Factors









Demographic Factors

Cluster 1

- Low personal income and GDP
- Small labor force participation
- Highest unemployment rate

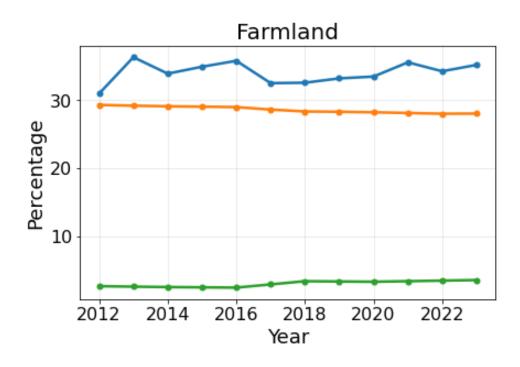
Cluster 2

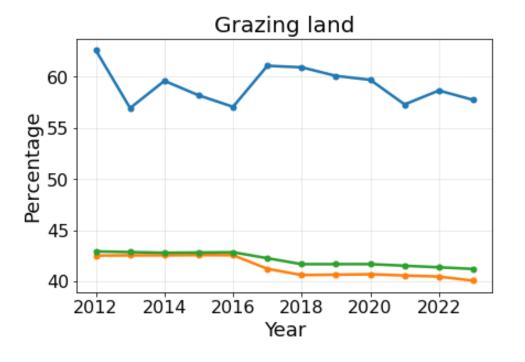
In between

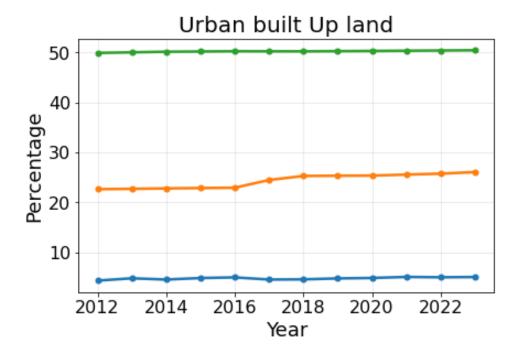
Cluster 3

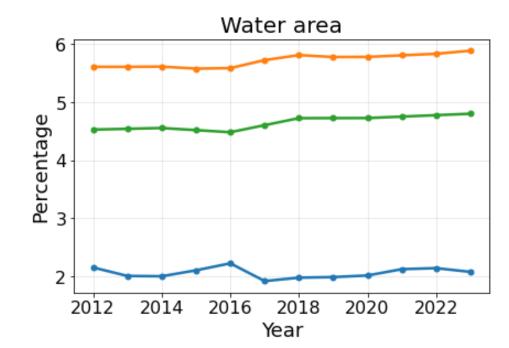
- High personal income and GDP
- Large labor force participation
- Lowest unemployment rate

Land-Use Factors









Land-Use Factors

Cluster 1

 The most rural with large % of agricultural and farmland

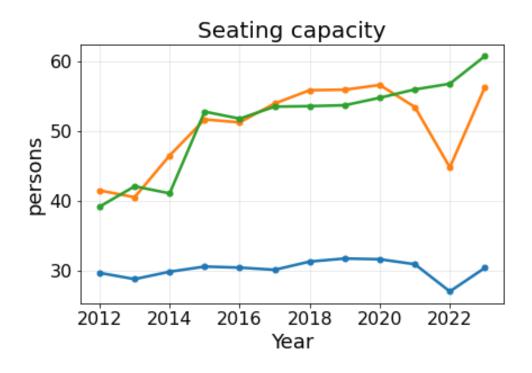
Cluster 2

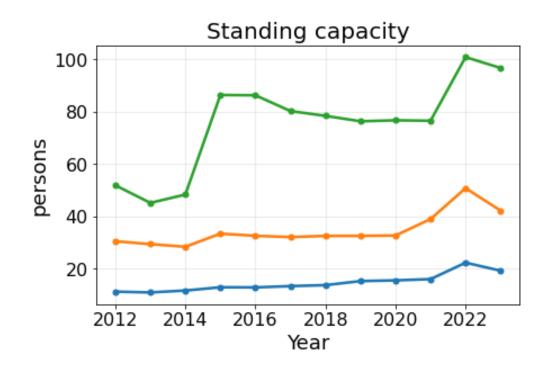
In between, suburb

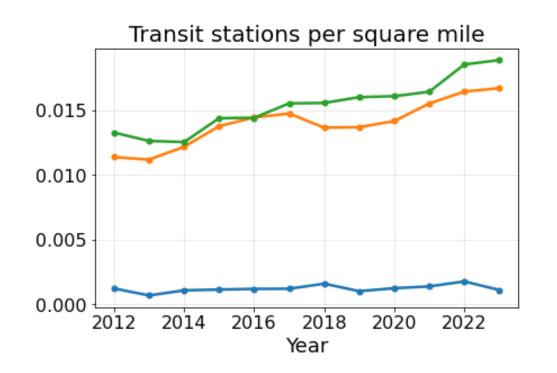
Cluster 3

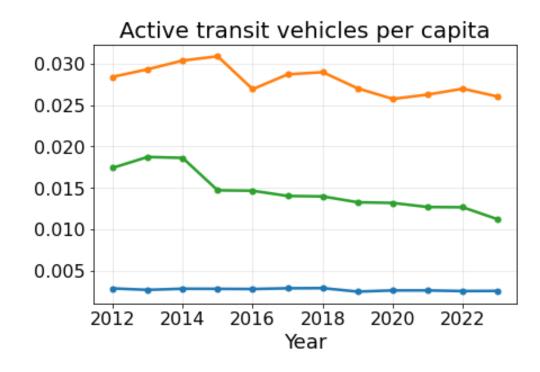
 The most urban with large % of developed and built-up land

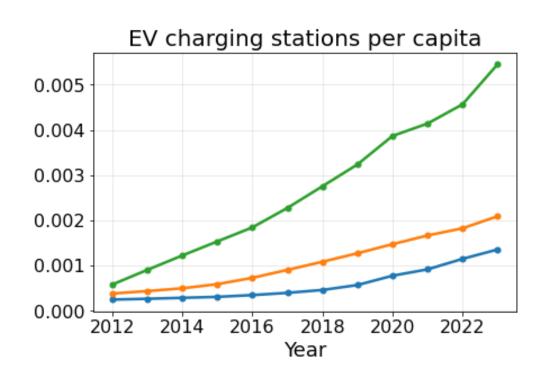
Infrastructural Factors













Infrastructural Factors

Cluster 1

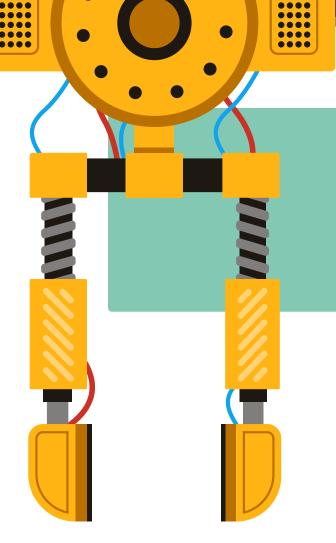
 Few charging stations and lowcapacity transit network

Cluster 2

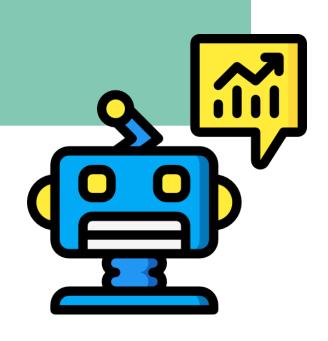
In between

Cluster 3

 The best transportation infrastructure, well developed transit network with high charging station number

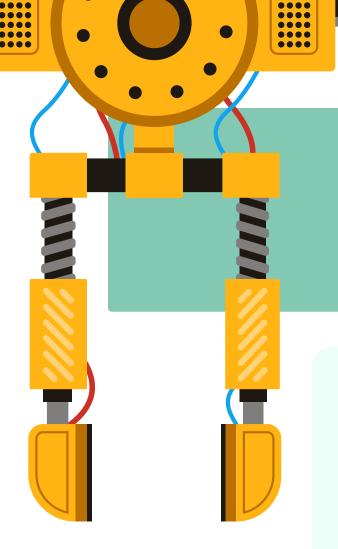


Phase Two





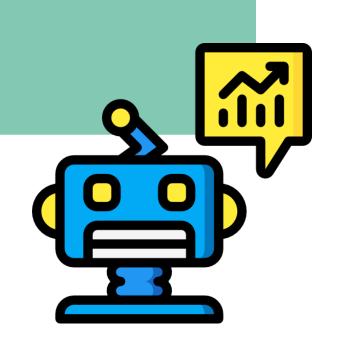




Phase Two











What did we find?

Random Forest Model Results

- **Accuracy:** 78%
- Influencing factors: demographic factors such as race, foreign-born share, and education

American Indian and Alaska Native

Bachelor's degree or higher

Personal income per capita -

Average standing capacity -

Labor force share of population

Active transit vericles per capita

Less than high school graduate

EV charging stations per capi

Transit stations per square mile

Single female householder

Hispanic or Latino origin

Some college or associate's degree Non-English language speakers

Native Hawaiian and Other Pacific Islander

Married couple family

Grazina

Living alone

Median age

Water area

White -

0.0

0.2

High school grad ate, GED, or alternative

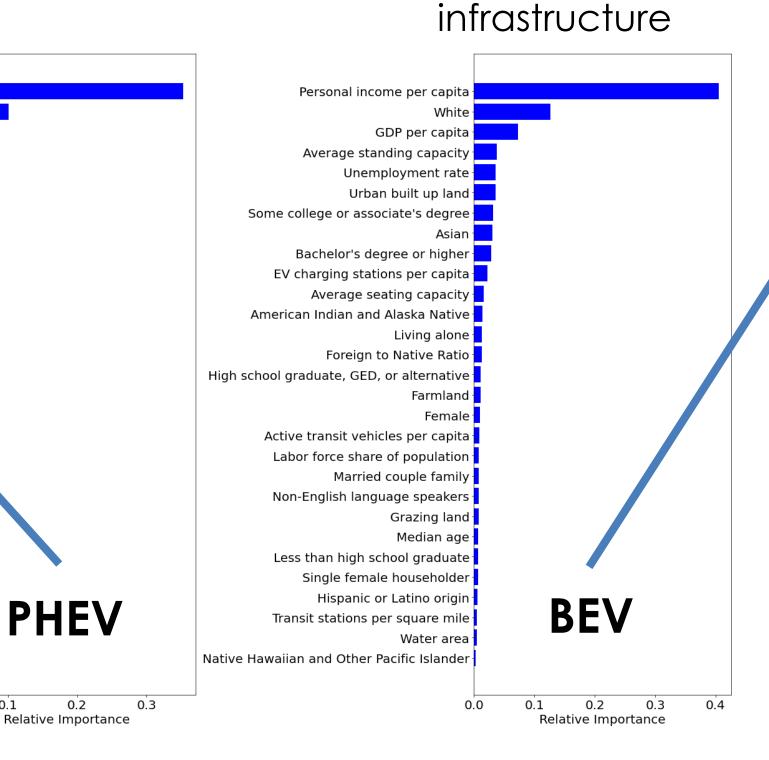
Unemployment rate

Foreign to Native Ratio

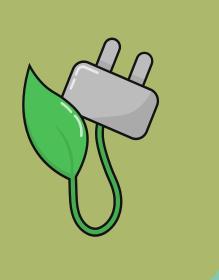
Urban built up land

GDP per capita

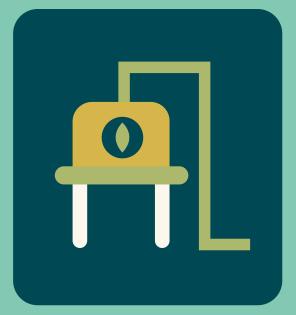




Conclusion



Counties show distinct EV rebate participation patterns over time.



Higher adoption is tied to stronger economies, higher education, racial diversity, and urban infrastructure.

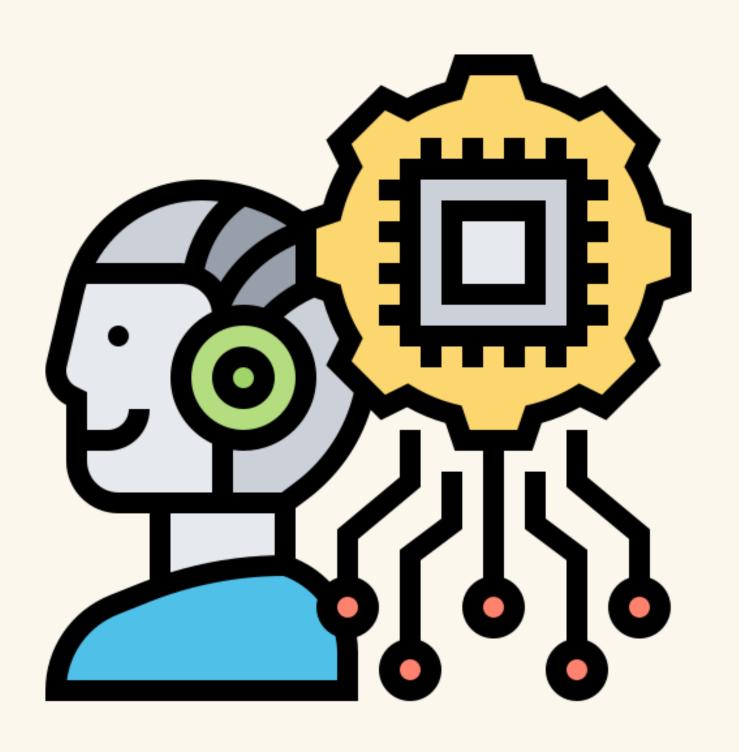


Rural, older, and lowerincome counties face persistent barriers despite rebates.



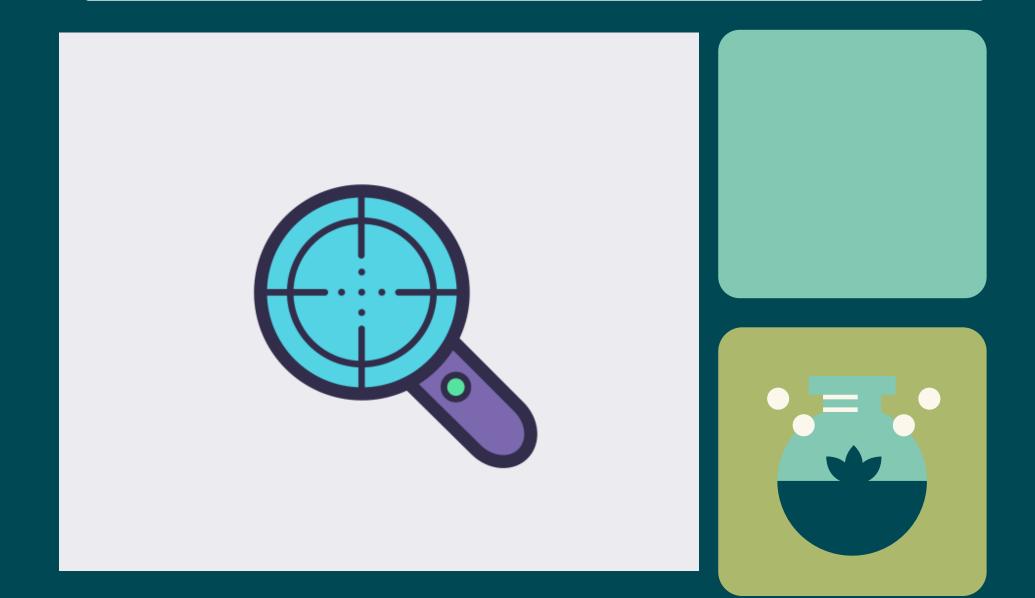
Targeted infrastructure, financial support, and outreach are more effective than uniform statewide incentives.

Study Importance



Shows how advanced techniques can guide more targeted, datadriven policy planning beyond uniform statewide approaches.

Next steps



Integrate post-2023 data to capture the influence of emerging technologies, policies, and funding structures on EV adoption

Thank you!

Questions?





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LinkedIn: @heli-mohamadi

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