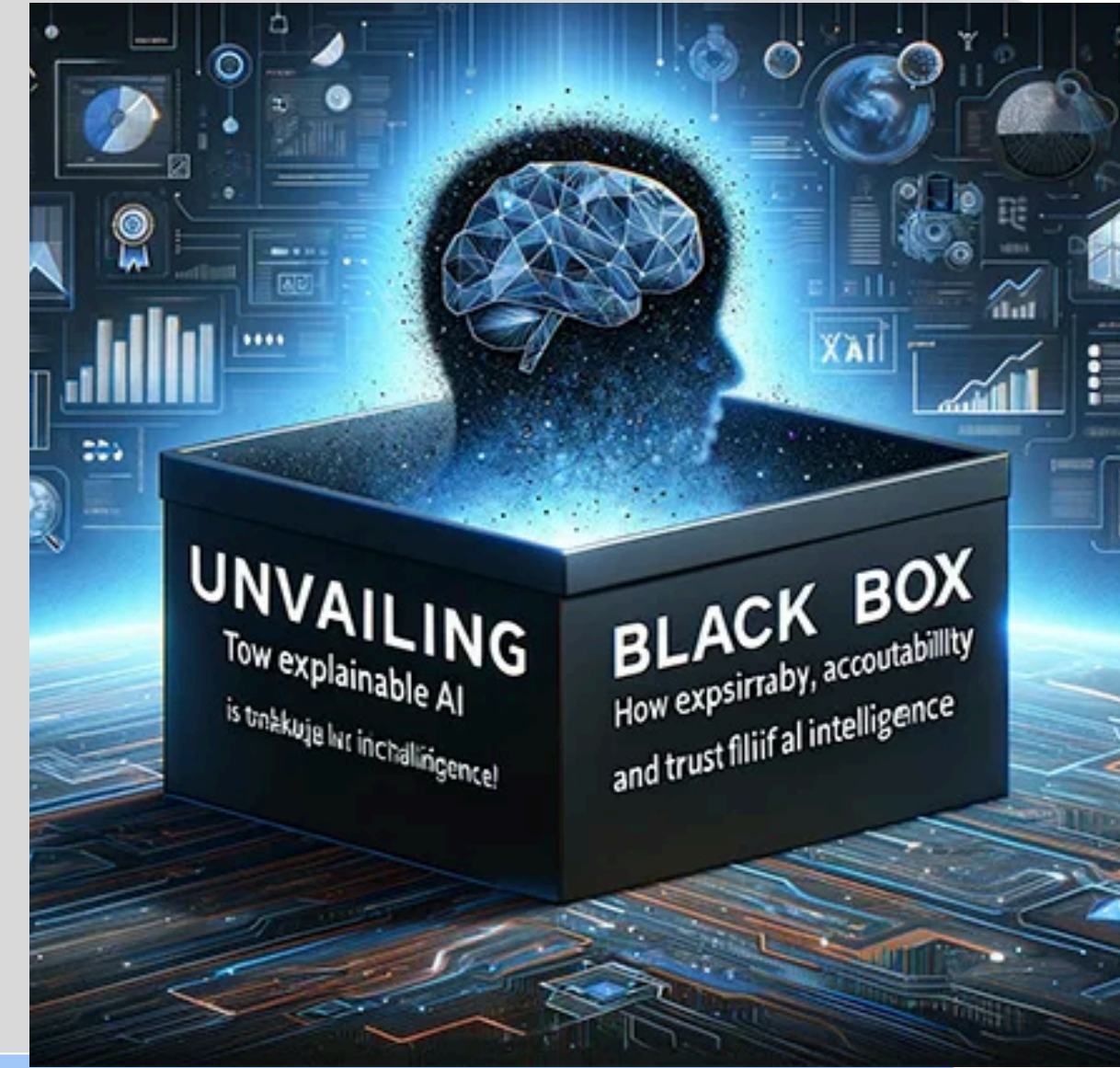


# RESHAP THE ENERGY SYSTEM

Philip Cai | MCOMP | philipcai0909@gmail.com

Host Supervisor:  
Dr Firouzeh Rosa Taghikhah

Academic Supervisor:  
A/Prof Penny Kyburz



**SHapley Additive exPlanations (SHAP): An Explainable Artificial Intelligence (XAI) method in Machine Learning (ML) that assigns each feature an importance value for a particular prediction, based on the concept of Shapley values from cooperative game theory. This technique decomposes a prediction into the contribution of each feature, helping to explain the output of complex models in a fair and consistent way.**

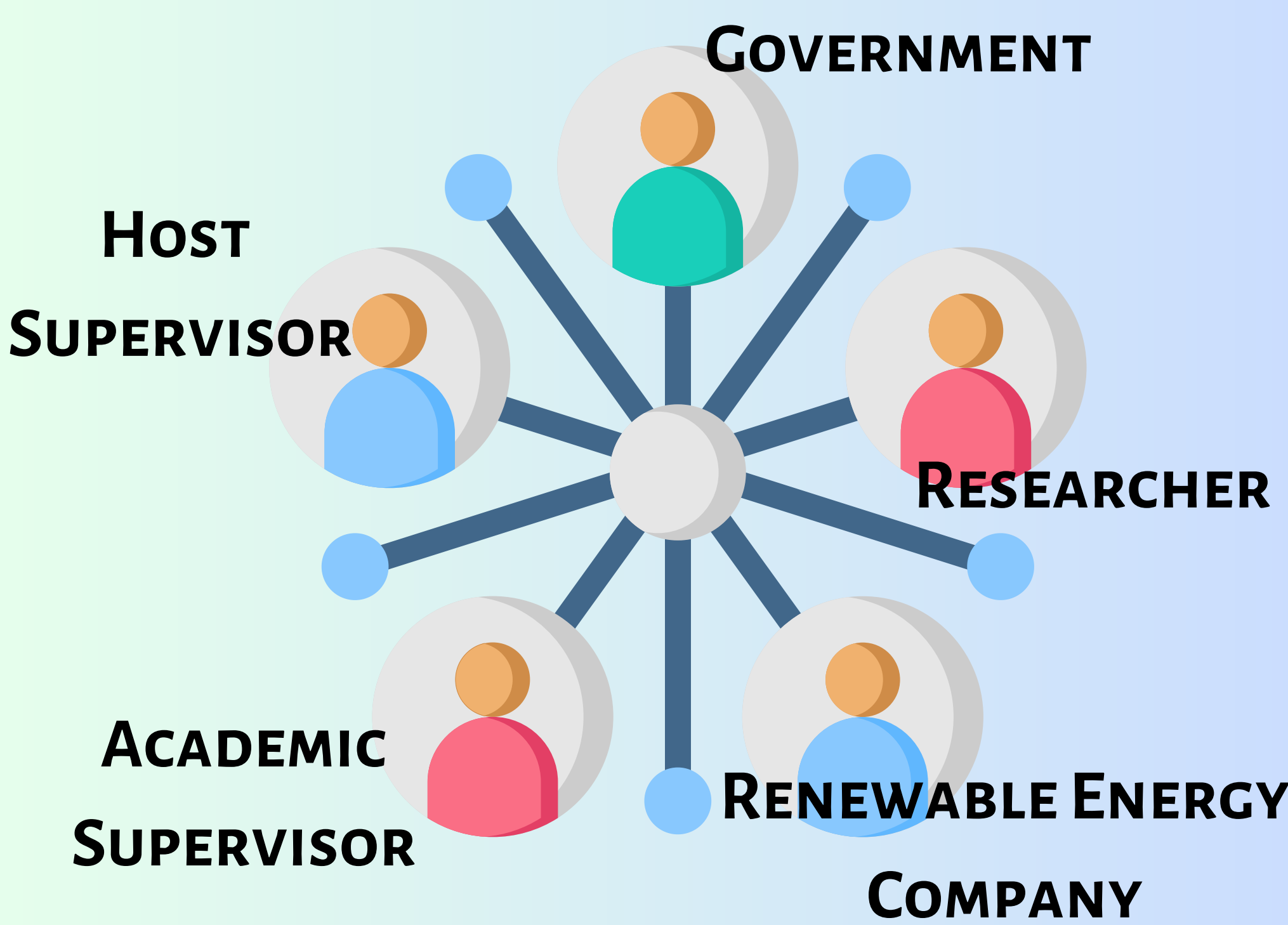
## PROJECT SCOPE

This project will develop machine learning models to accurately predict community participations on renewable energy systems using a survey dataset, incorporating Explainable Artificial Intelligence (XAI) methods, particularly SHAP explainers, to ensure transparency in AI decision-making. By enhancing the interpretability of ML processes, the project aims to demystify machine learning models, thereby increasing stakeholder trust and supporting the broader adoption of renewable energy initiatives.

## PROJECT OBJECTIVE

- Develop Optimal Machine Learning Models
- Enhance Transparency and Interpretability in ML processes
- Increase Stakeholder Trust
- Support Renewable Energy Adoption

## STAKEHOLDER



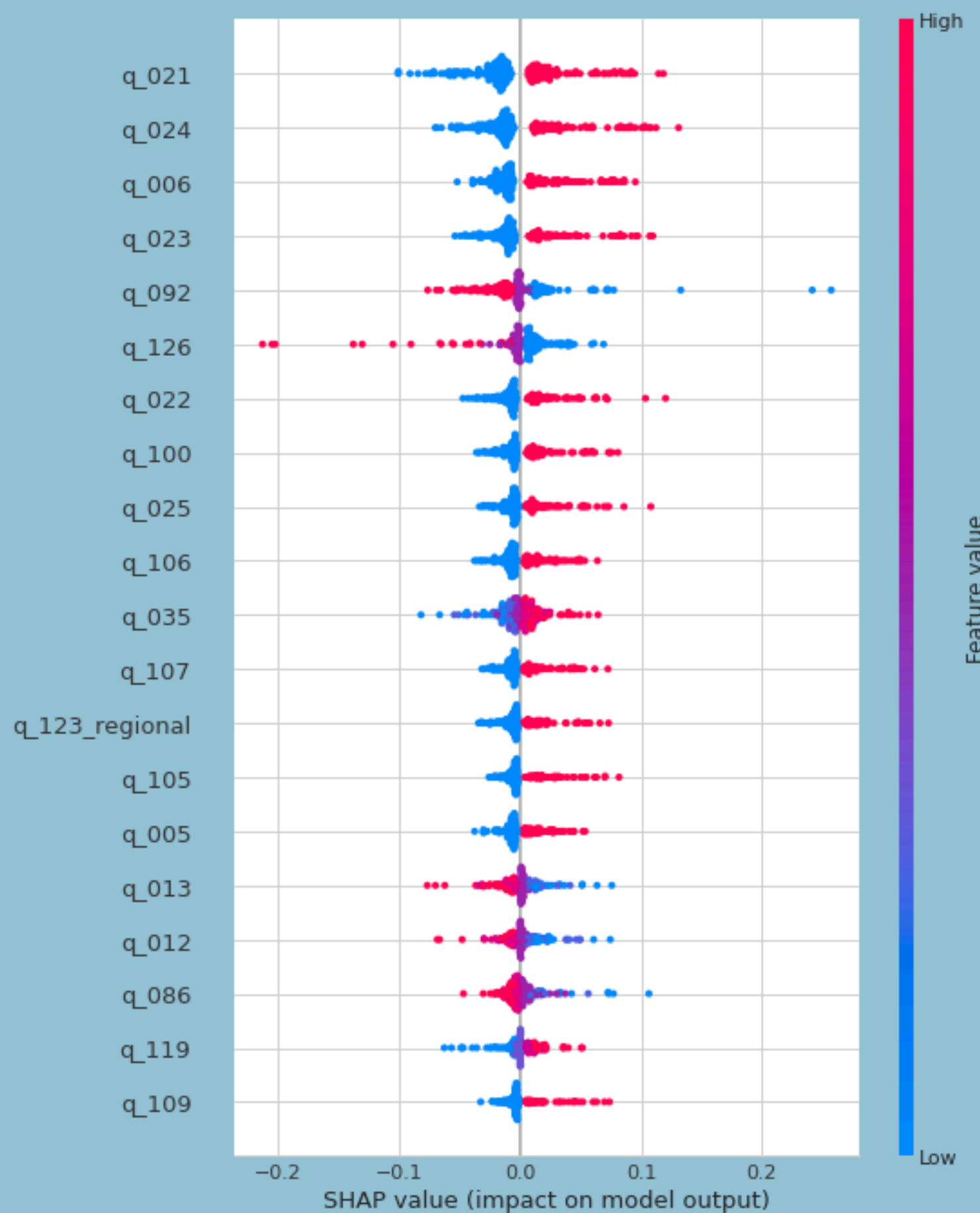
## METHOD

1. Preprocessing dataset and define independent & target variables. Prediction is made on participation levels of renewable energy (Low, Medium and High).
2. Define Models including Random Forest, XGBoost, MLPClassifier and Keras Neural Network, perform hyperparameter tuning.
3. Evaluate Model and Select the best two models
4. Fit SHAP KernelExplainer and DeepExplainer on Two Models Respectively.
5. Evaluate explanation quality for both pairs, then select the optimal Model and Explainer pair for final interpretation.

## RESULTS

- MLPClassifier and Keras Neural Network are two best performing models (both are neural network).
- **SHAP KernelExplainer for MLPClassifier** produces more robust and stable explanations than the DeepExplainer for Keras Neural Network.
- The top 3 Influential features are
  - whether or not facing **electricity grid issues** (q\_030)
  - whether or not having **renewable energy installed** (q\_021)
  - whether or not wanting to **generate renewable energy** (q\_025)
- The features influence class predictions differently. For example, having renewable energy installed (q\_021), planning to install renewables (q\_024), supporting medium & large scale corporate-owned renewables projects to achieve renewable energy target (q\_006) etc primarily drive the predictions to High Participation.

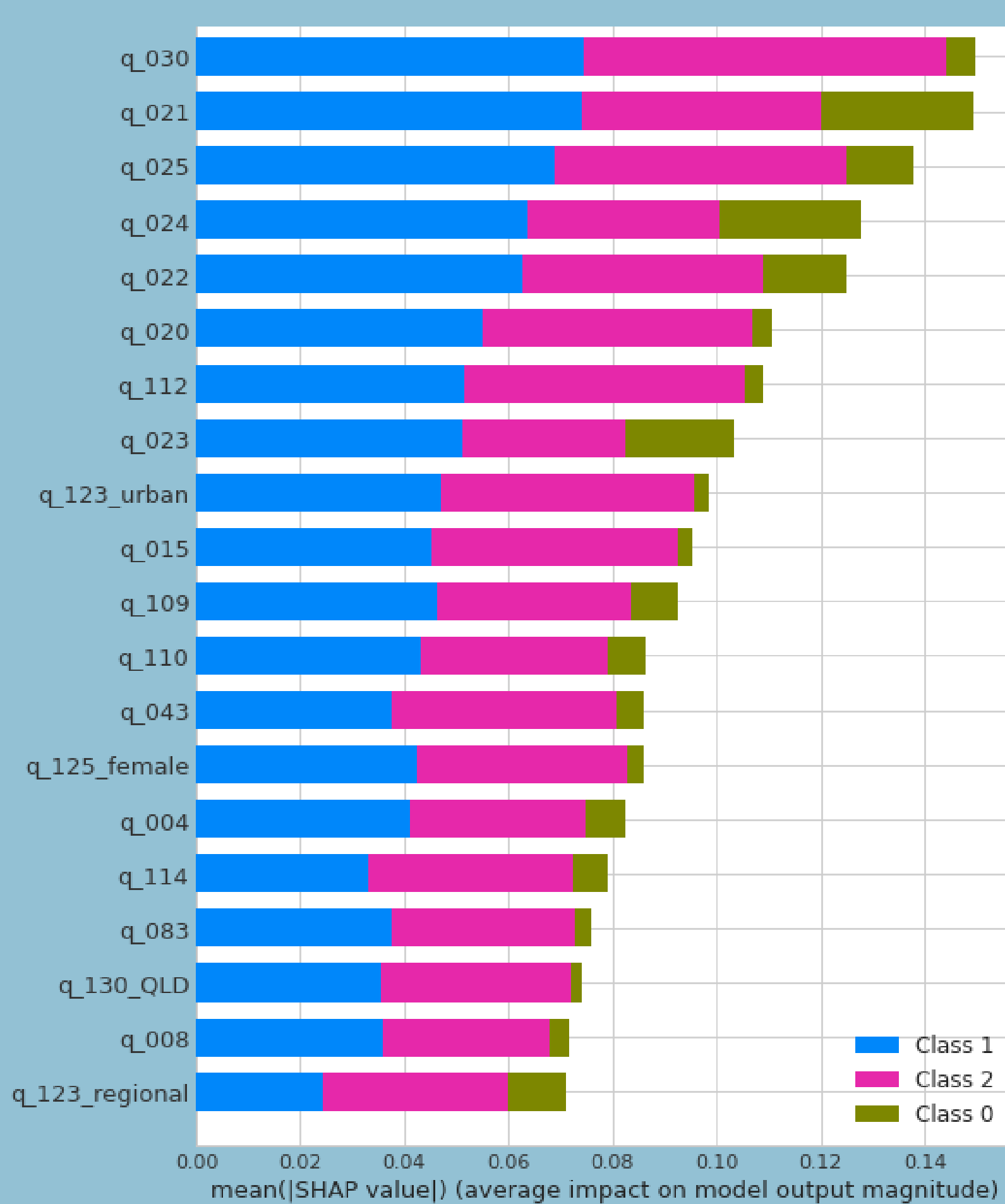
## SHAP SUMMARY PLOT



## DISCUSSION

- **DeepExplainer:** Designed for deep learning models, it uses internal gradient calculations to compute SHAP values, which may increase its sensitivity to noise due to direct reliance on model intricacies.
- **KernelExplainer:** Approximates SHAP values using a model-agnostic surrogate model, estimating feature contributions through sampling. This approach makes it less sensitive to data perturbations and more robust against model changes.
- **Computational Efficiency:** While KernelExplainer offers robustness, it requires extensive computational time due to its need to perturb all combinations of features for analysis. DeepExplainer enhances efficiency by using gradients to directly analyse the effect of input changes on the output.

## SHAP FEATURE IMPORTANCE PLOT



## BENEFITS

- Enhances predictive accuracy and transparency of community attitudes towards renewable energy.
- Builds stakeholder trust, crucial for the adoption of renewable energy projects.

## RECOMMENDATIONS

- Implement robust model validation processes to ensure reliable predictions.
- Maintain continuous engagement with stakeholders to refine models and encourage support for renewable energy initiatives.