

Multiple Sclerosis Treatment Effectiveness

Rea Burla

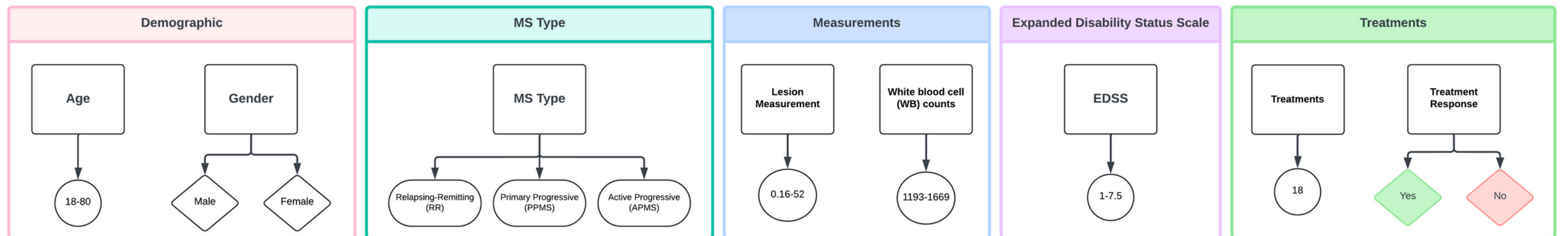
We examine the effectiveness of various Multiple Sclerosis (MS) treatments using several key metrics and patient characteristics, based on a dataset of 528 MS patients.

Dataset

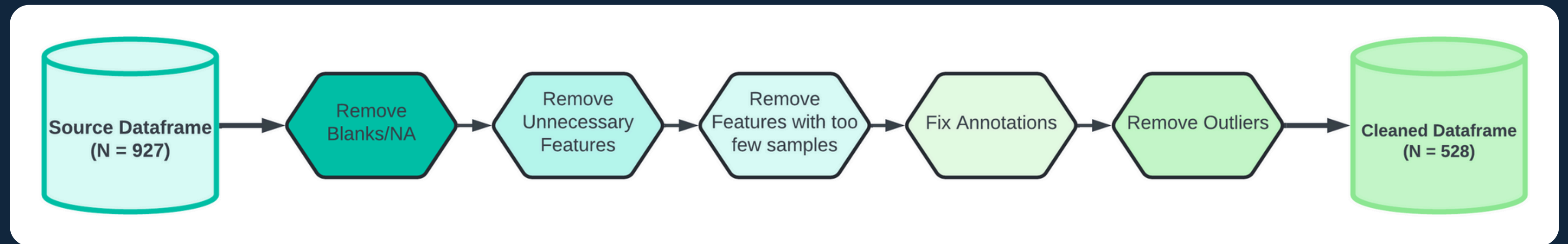
(Post-Cleaning)

The Dataset includes MS patients with various demographic and clinical characteristics.

This allows for analysis of treatment effectiveness across different patient profiles, MS types, and disability levels, providing valuable insights for personalized MS management strategies.

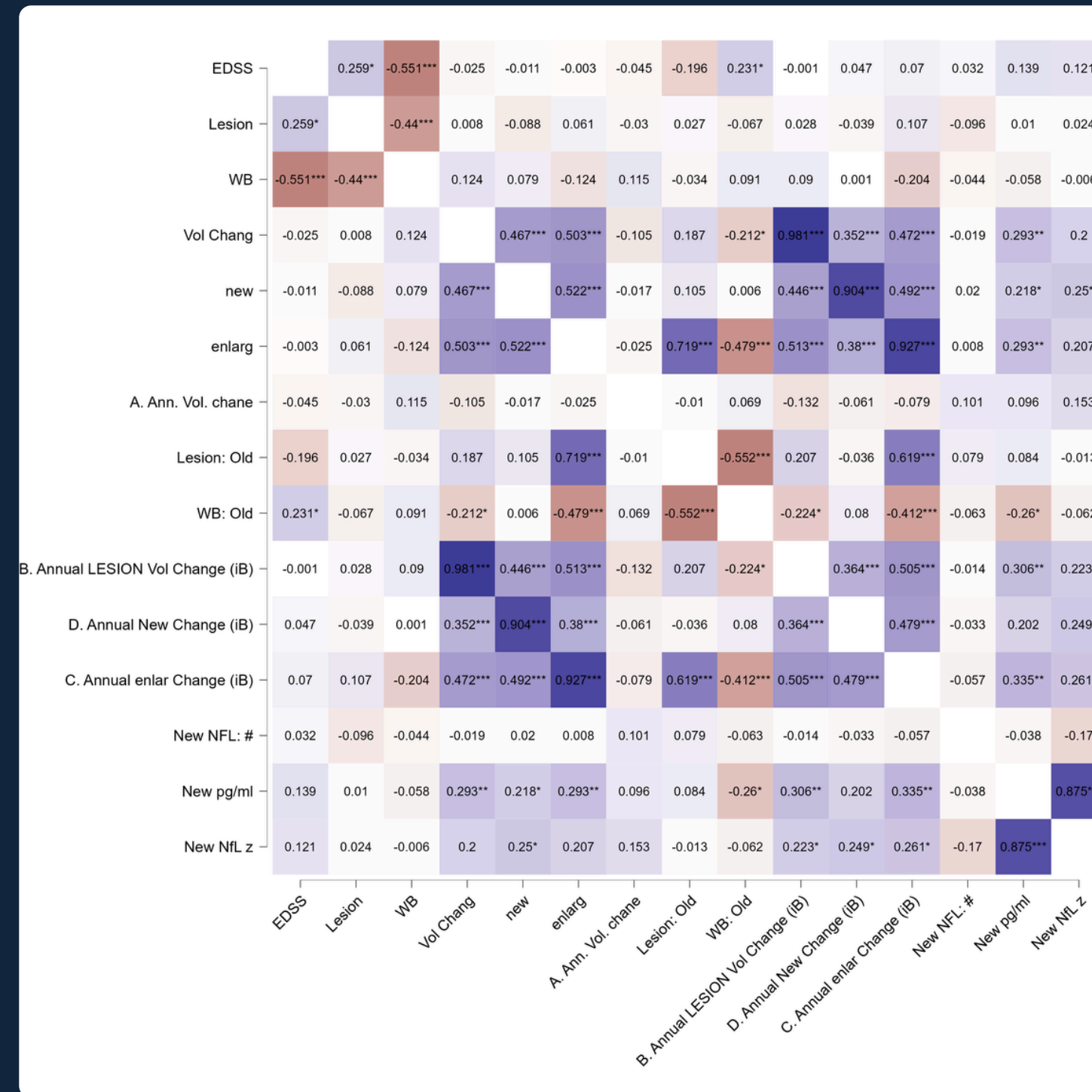


Data Cleaning



Data Cleaning

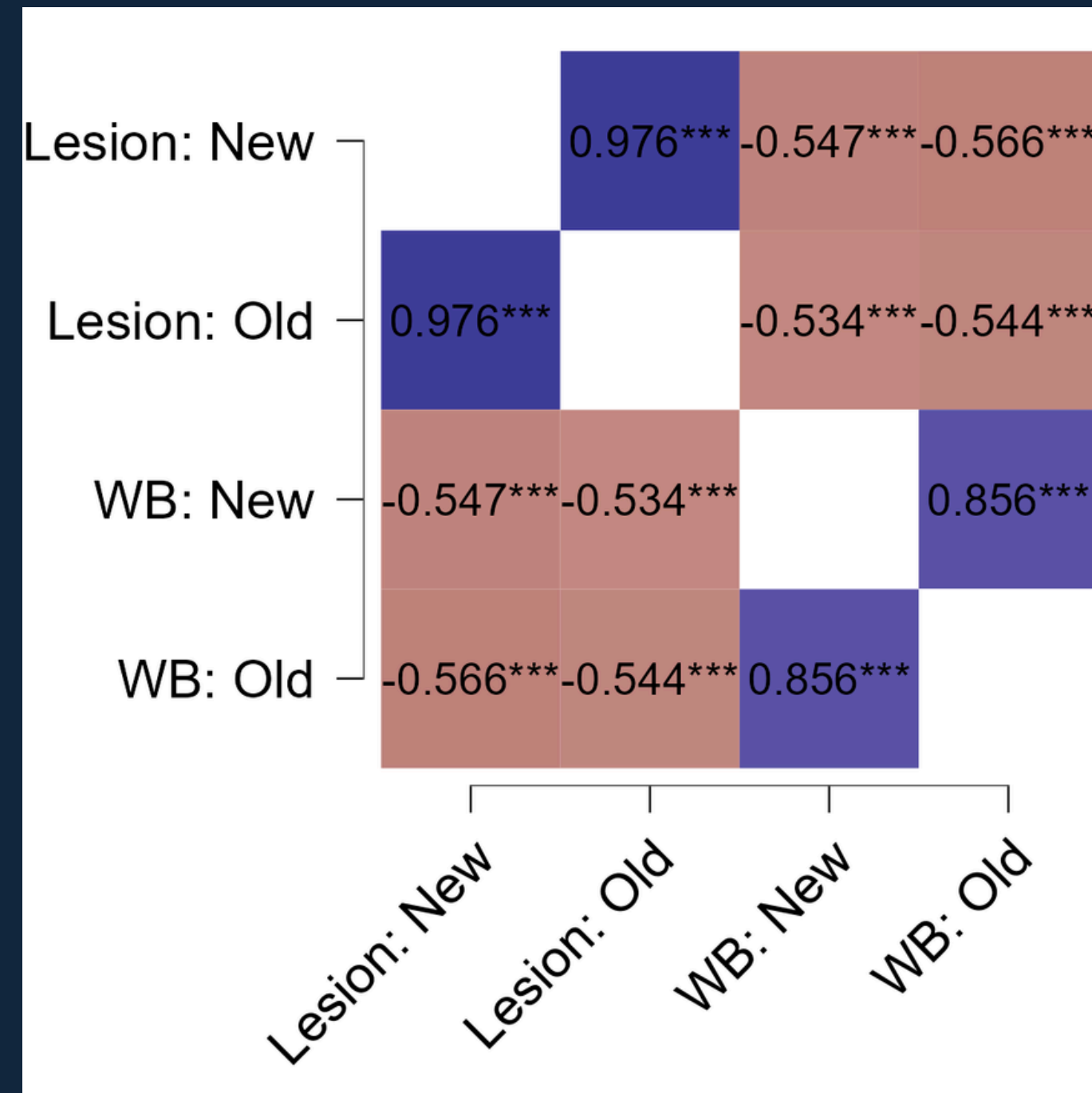
Spearman correlations



Removing features with high collinearity, or with too few samples ($N < 500$)

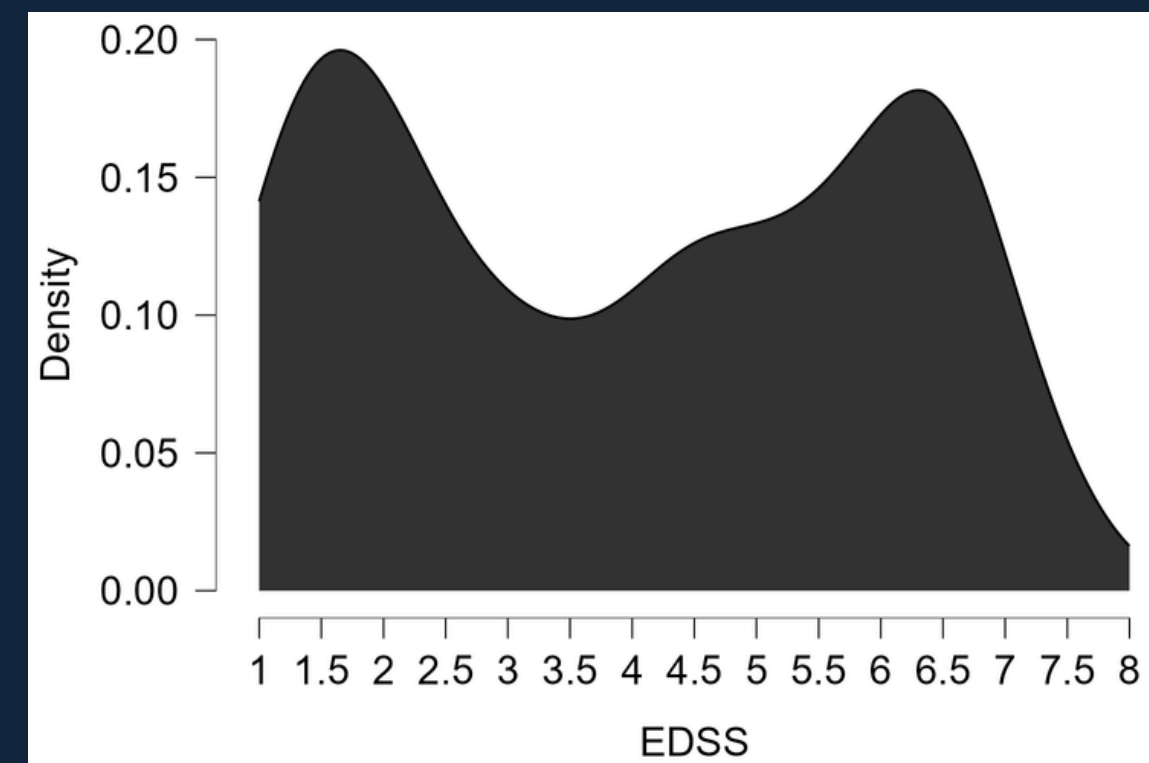
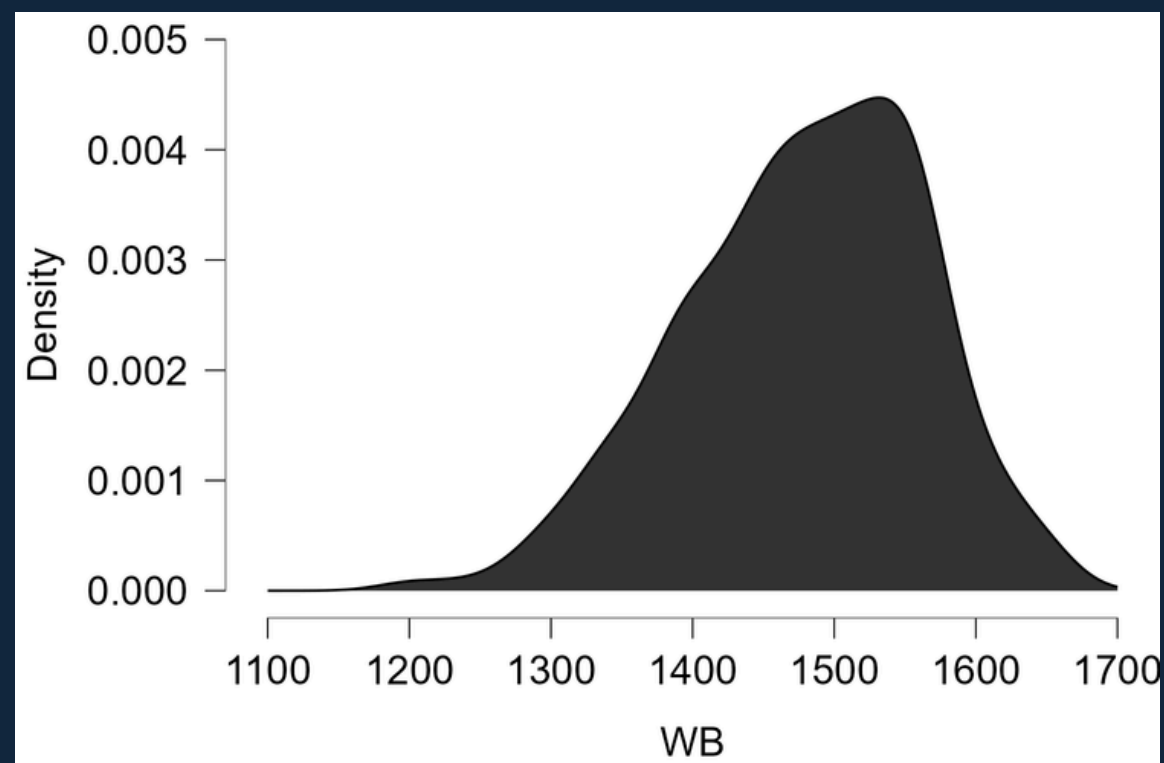
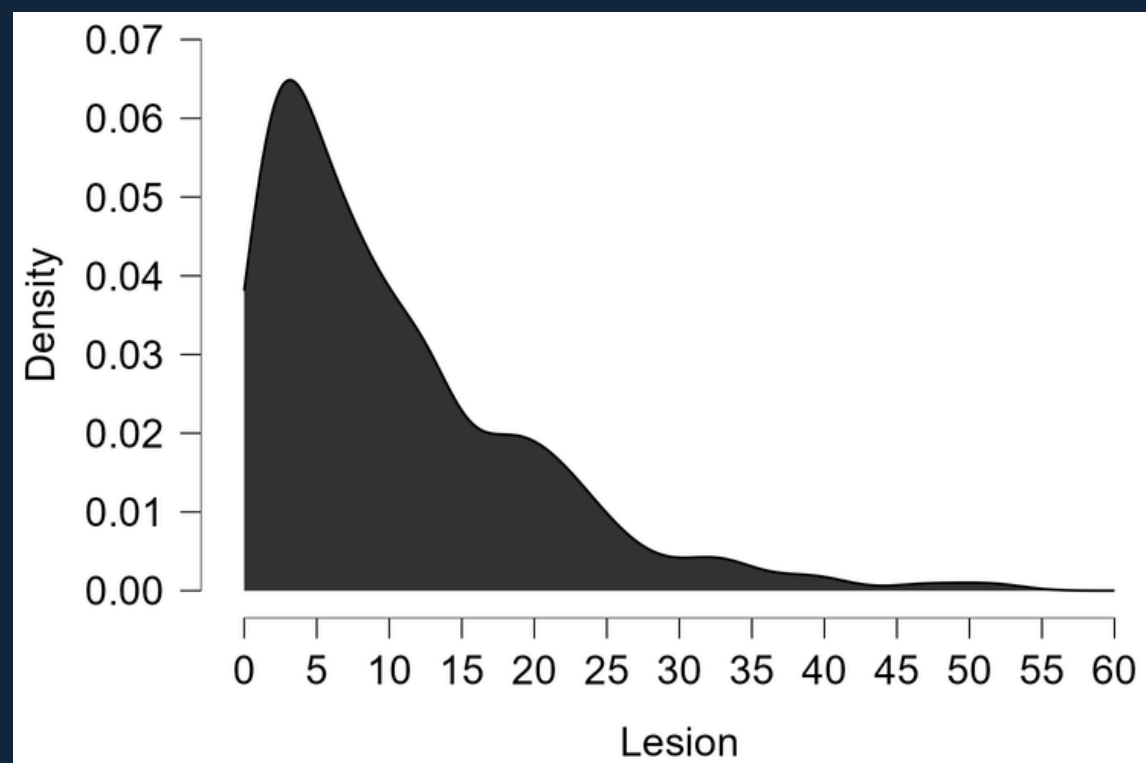
Data Cleaning

Spearman correlations



Due to high collinearity, we keep only the current/new measurements

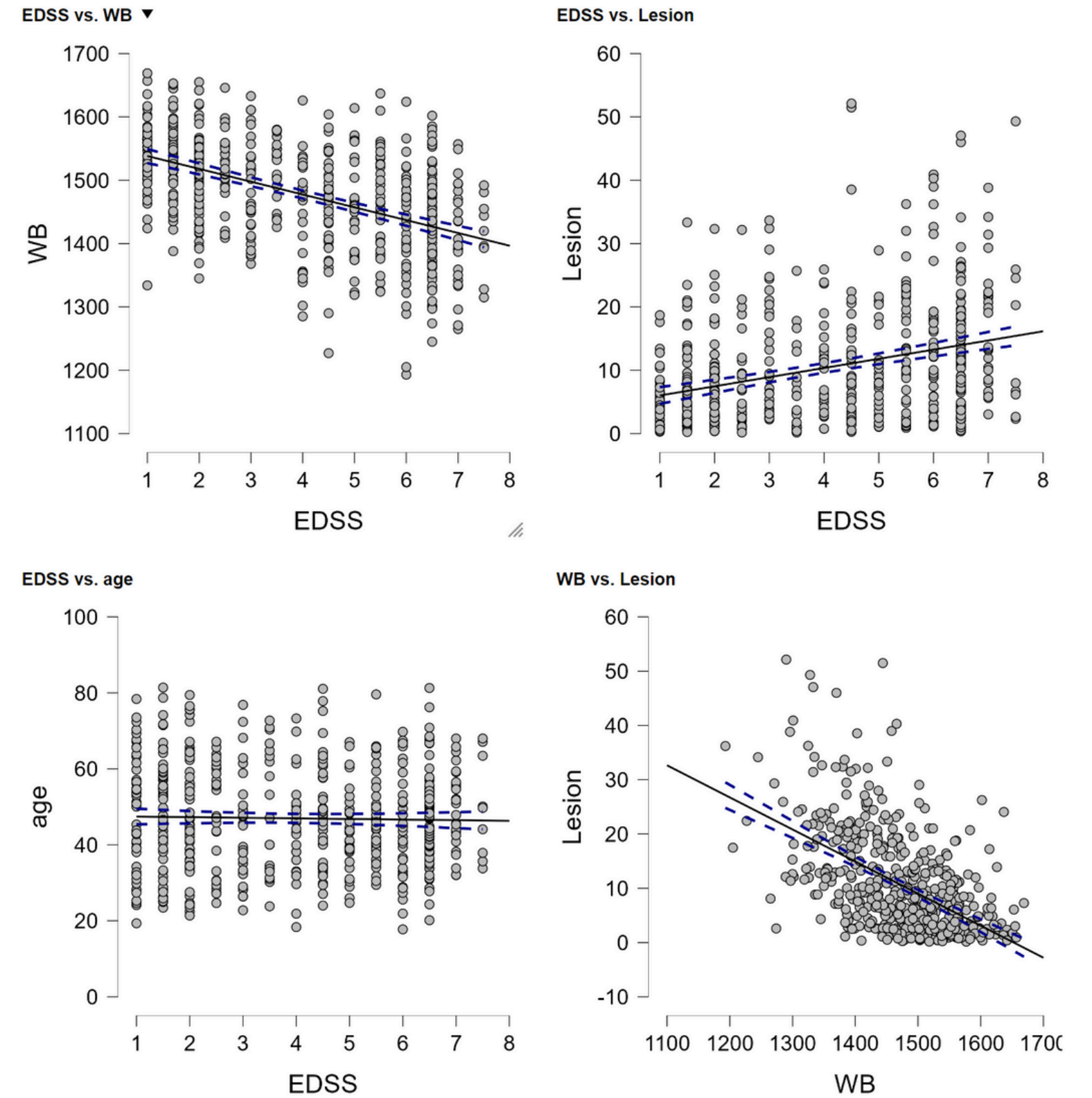
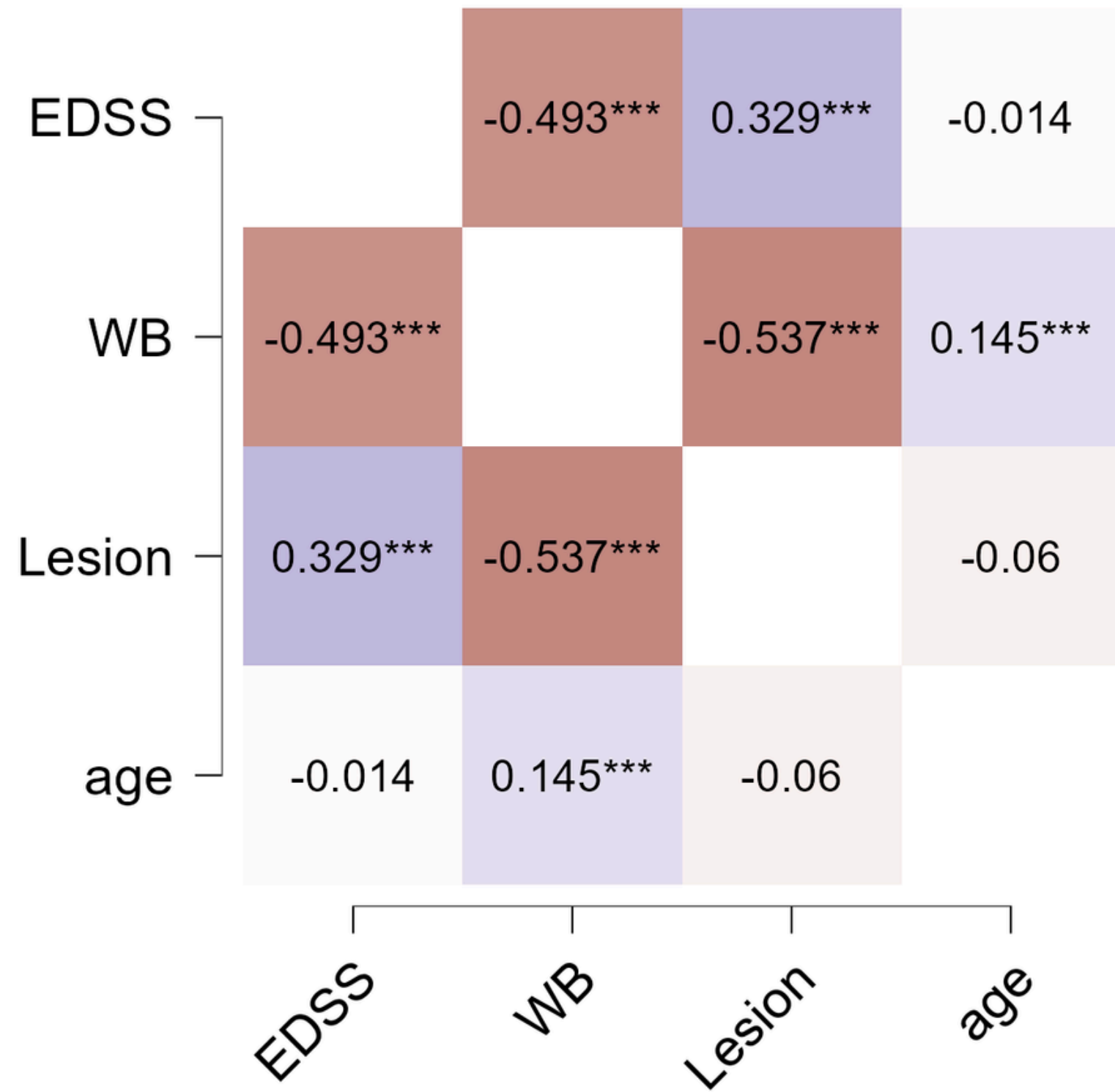
Data Distributions



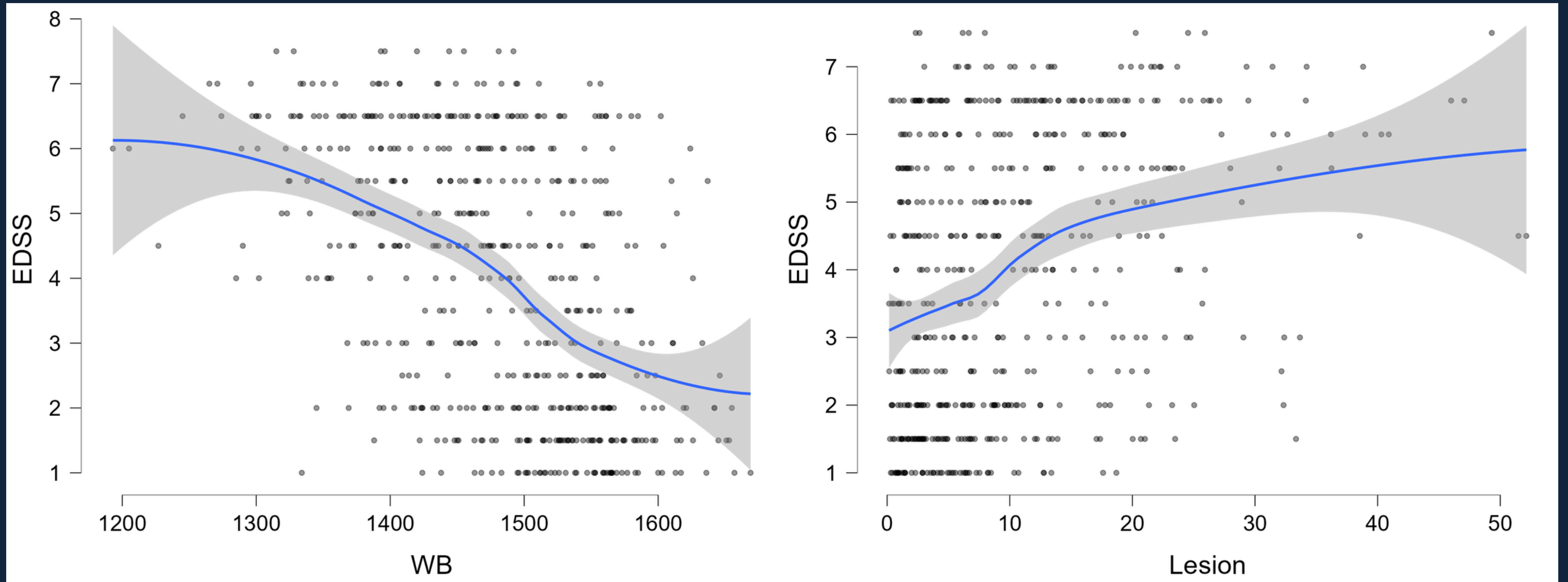
EDSS



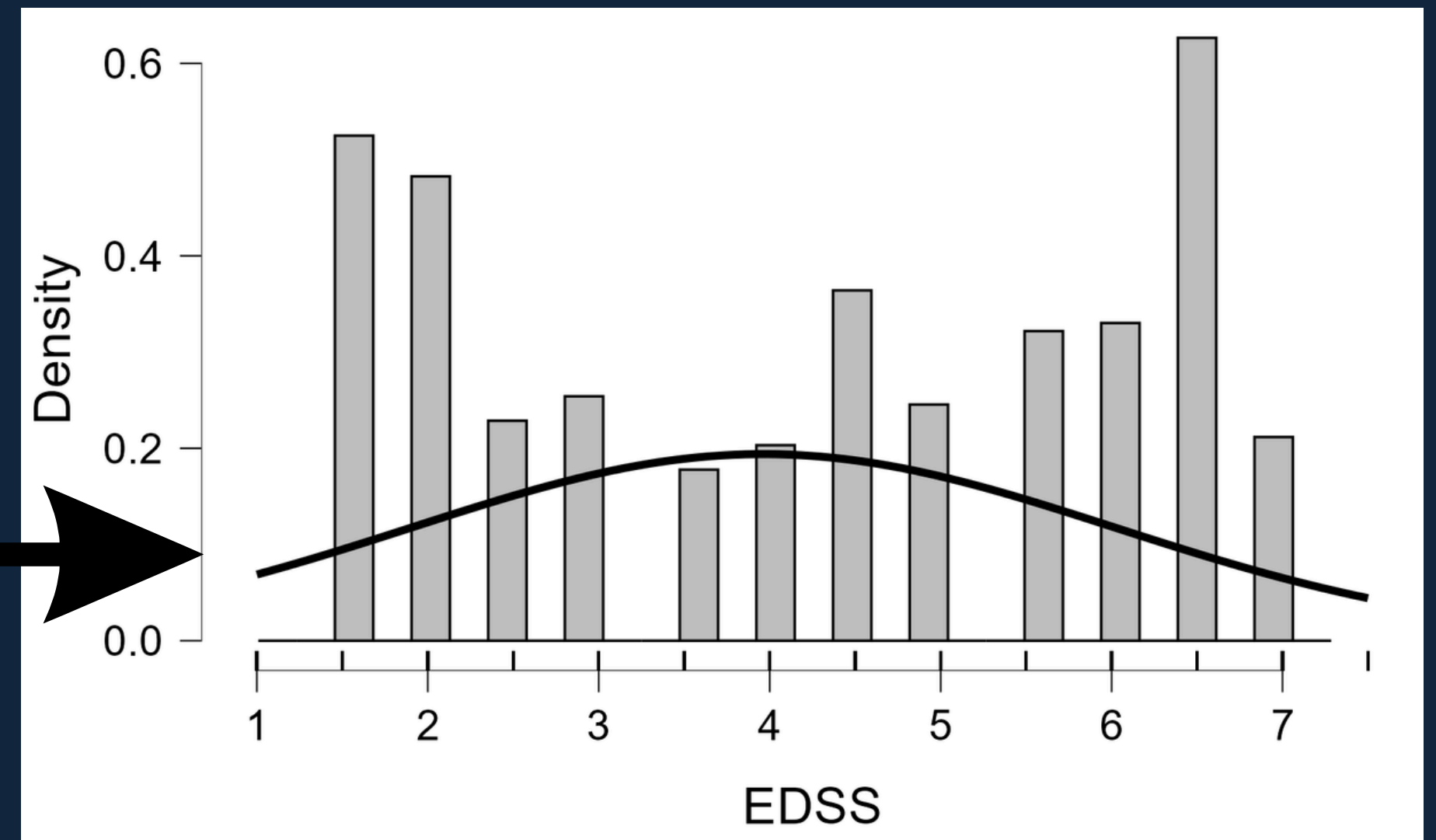
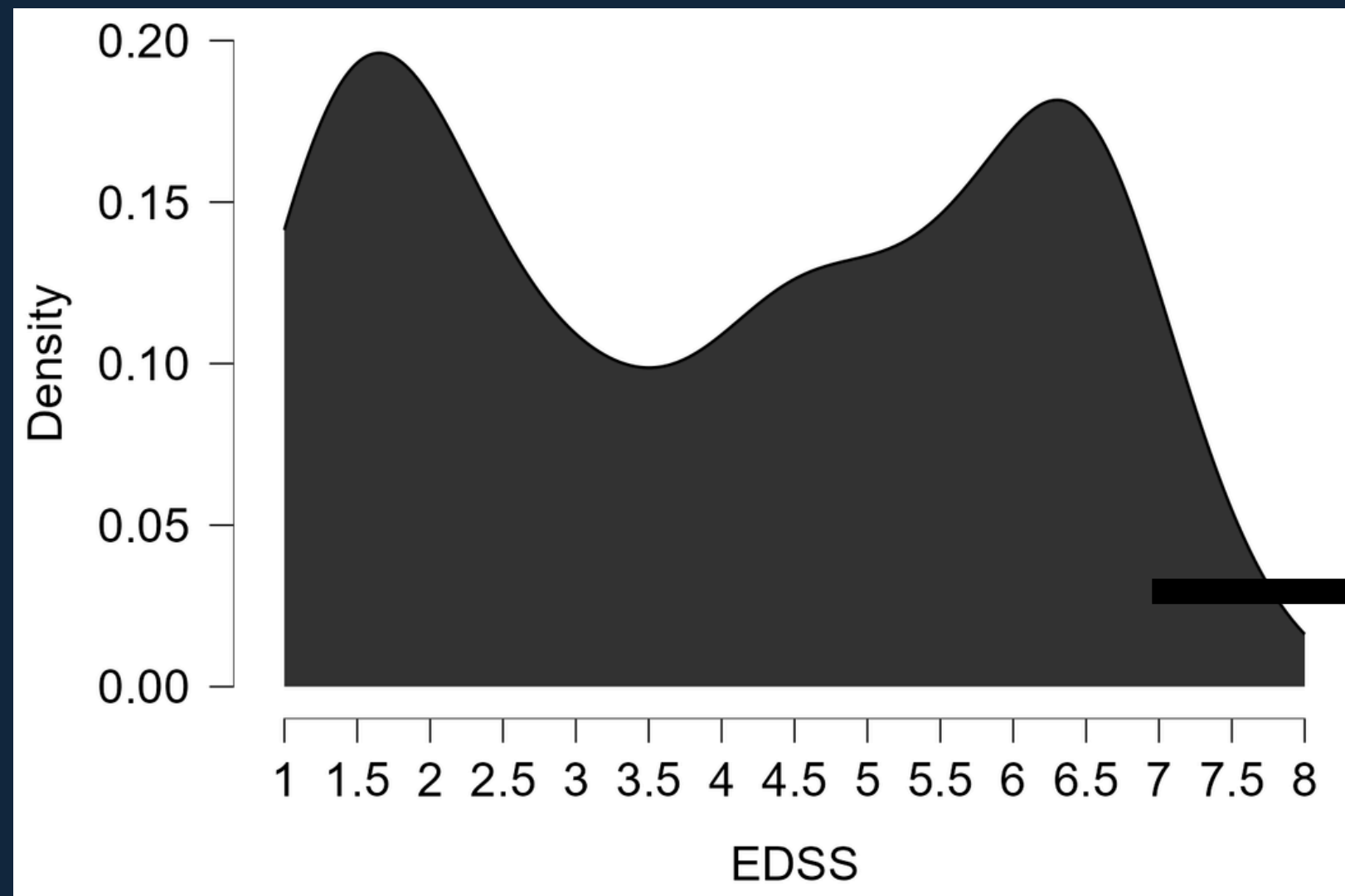
EDSS – Correlations



EDSS - Scatterplots



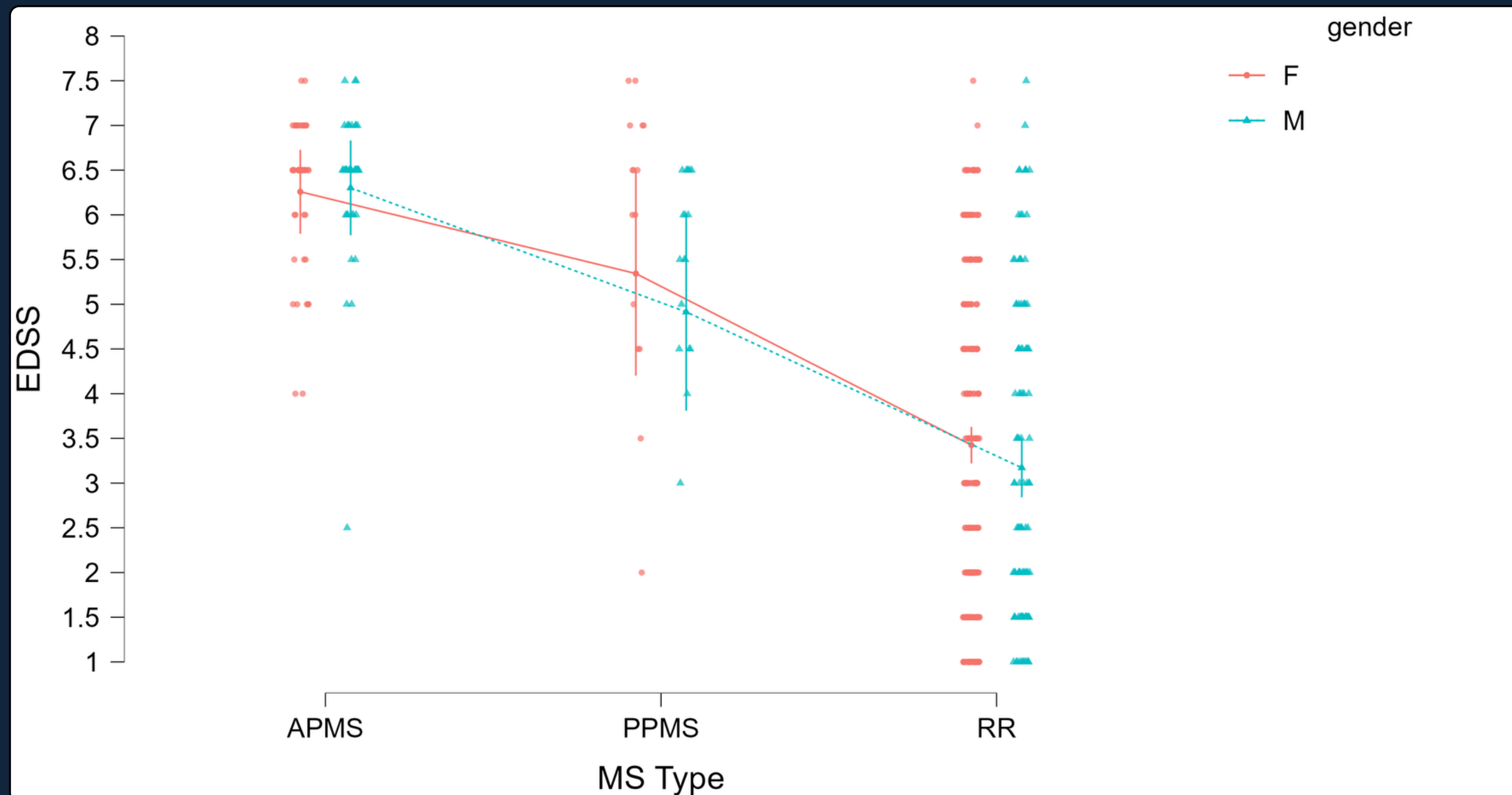
EDSS



EDSS is not normally distributed.

Predicting EDSS by MS Type and Gender

Generalized Linear Mixed Model (CI=95%)

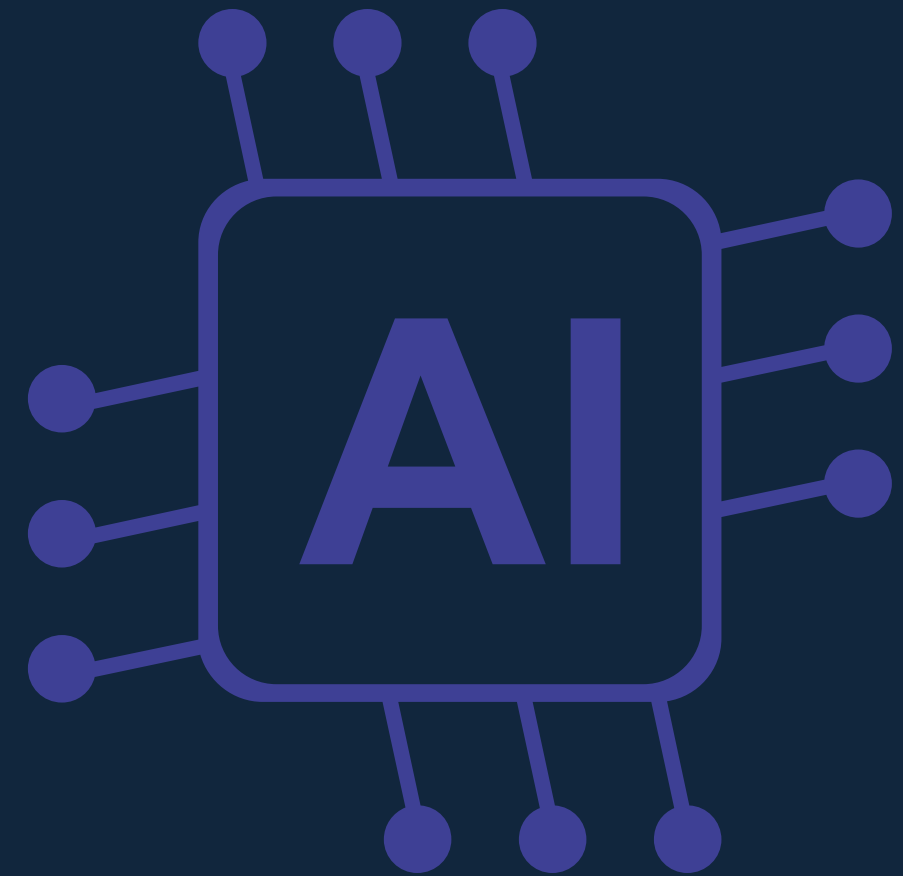


Using Machine Learning to Predict EDSS

A **Decision Tree Regressor** is ideal for predicting EDSS with limited features:

- Highly interpretable
- Non-Parametric
- Provides clear feature importance rankings
- Less likely to overfit on small datasets
- Aligns with clinical decision-making processes
- Computationally efficient

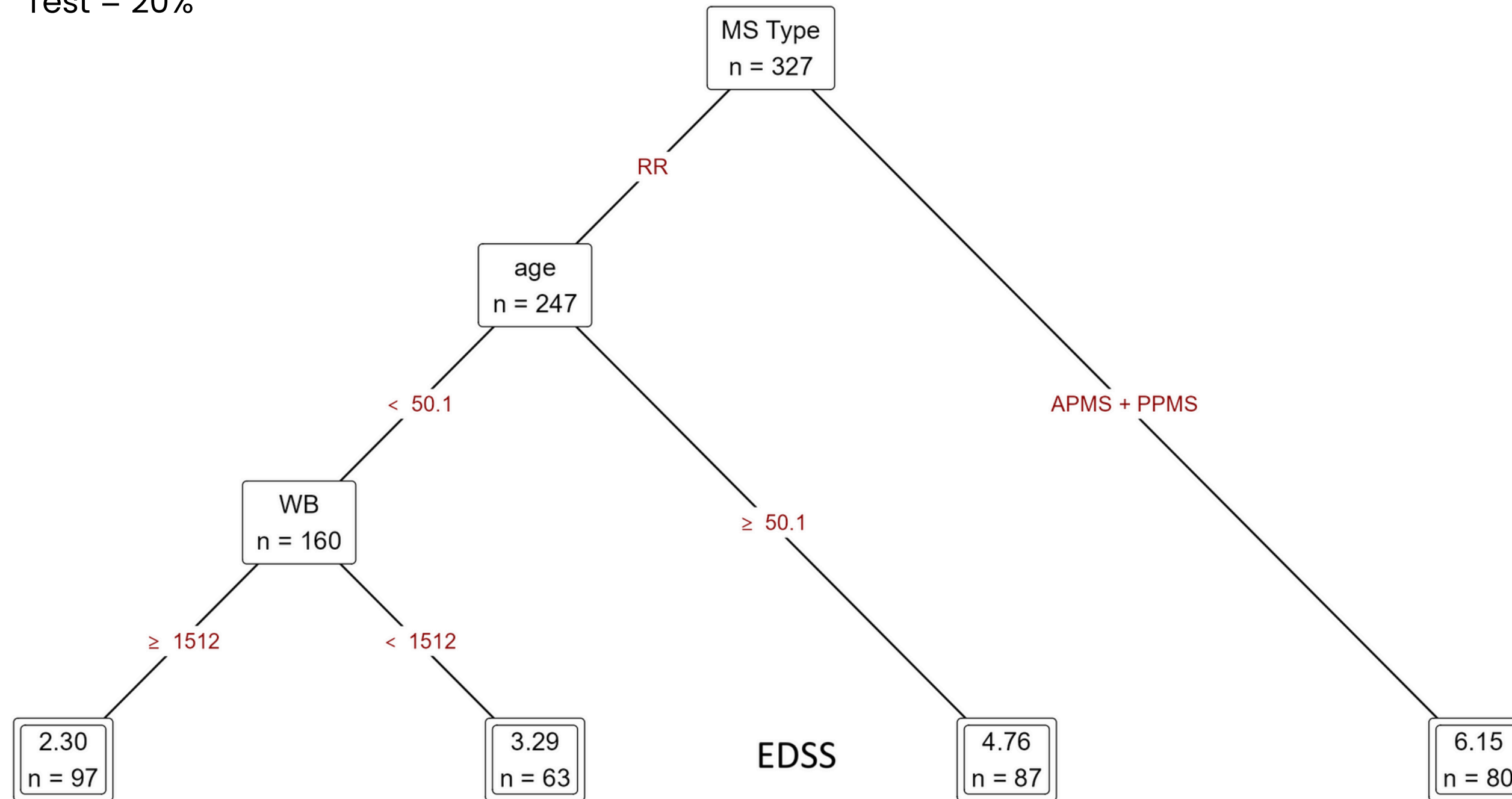
This simplicity and transparency make it a good starting point for modeling EDSS in Multiple Sclerosis patients, balancing predictive power with clinical usefulness.



EDSS Prediction (CI=100%)

Train = 80%

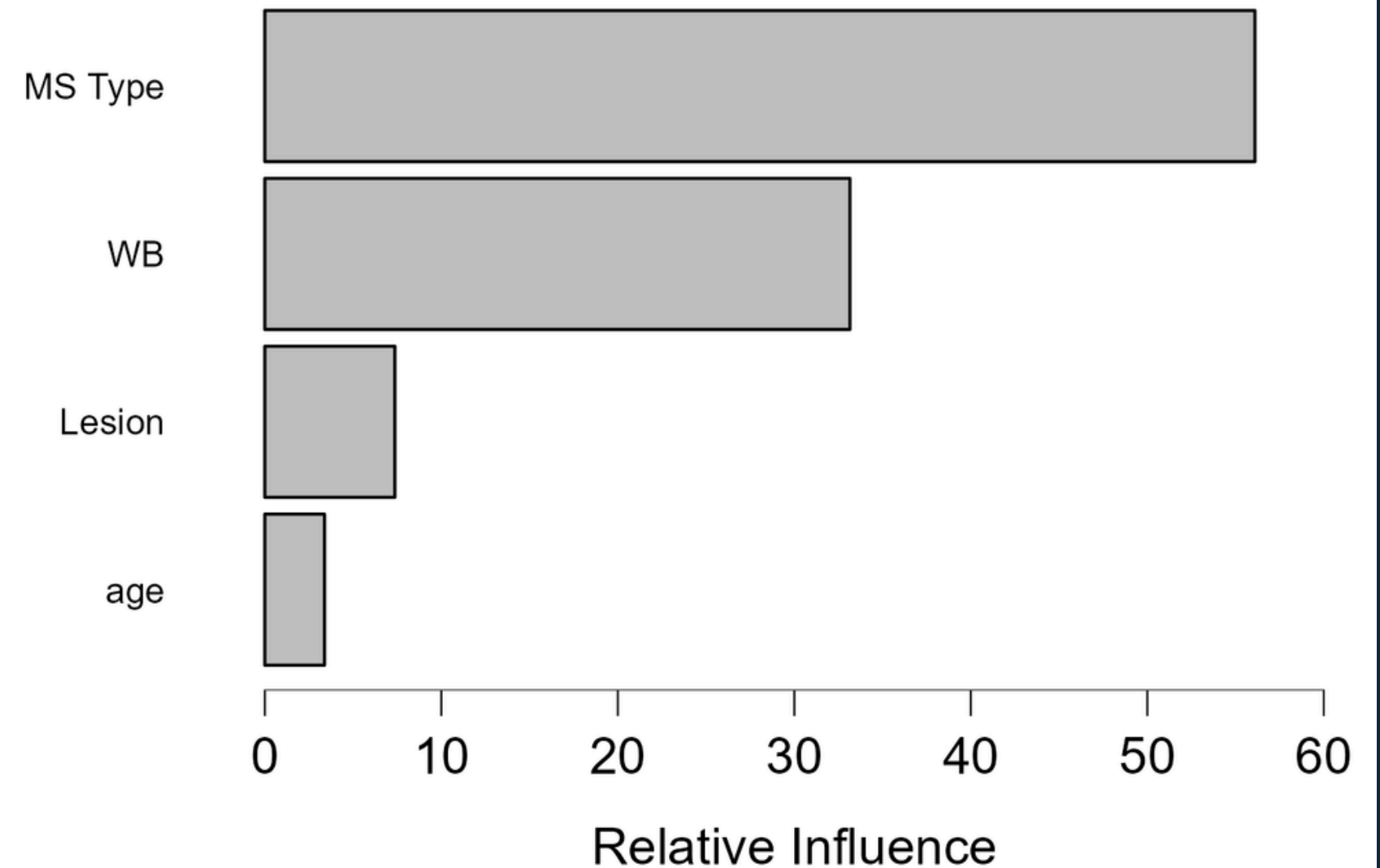
Test = 20%



Model Evaluation

Model Performance Metrics ▼

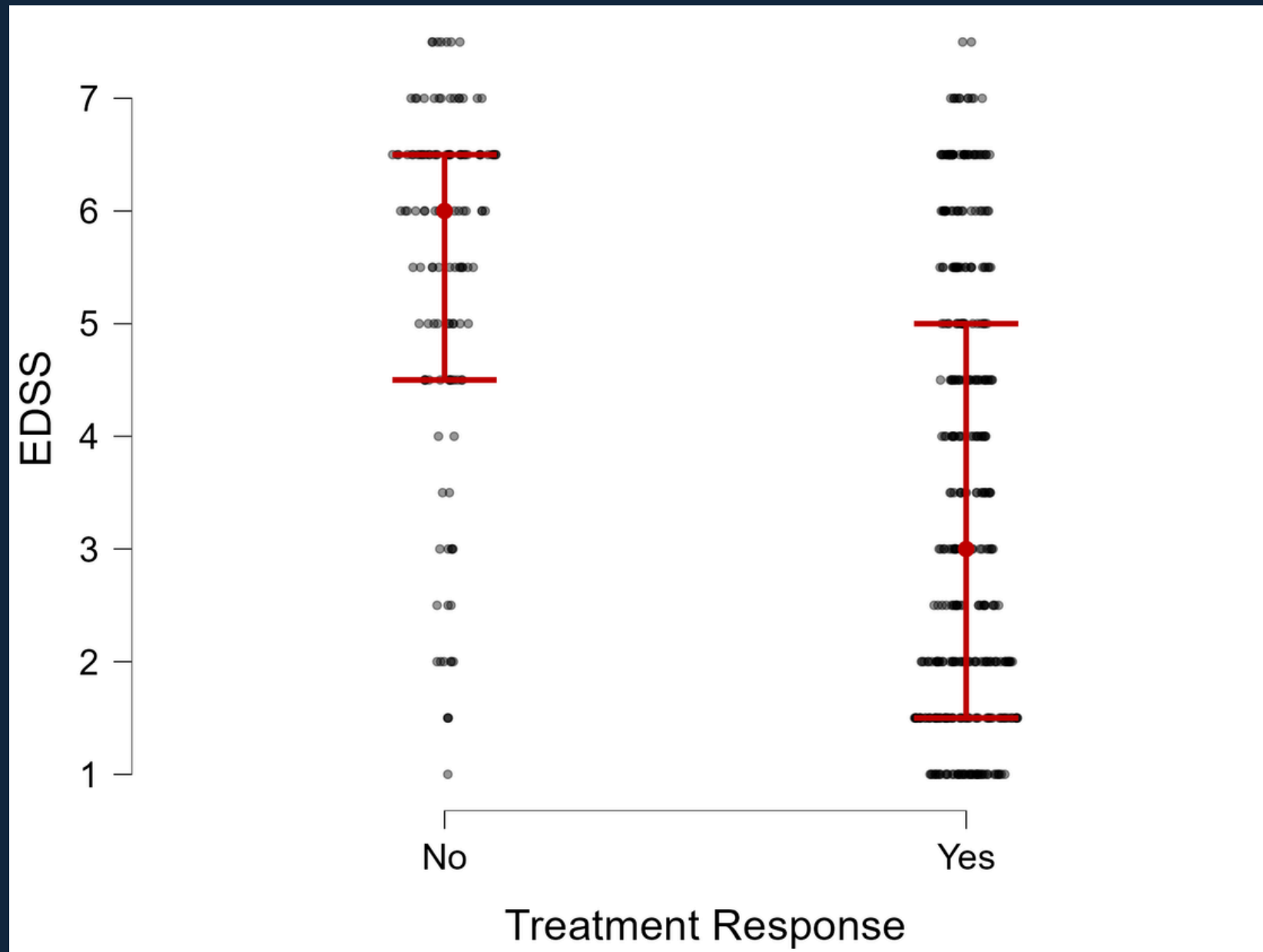
	Value
MSE	1.985
RMSE	1.409
MAE / MAD	1.133
MAPE	45.35%
R ²	0.581



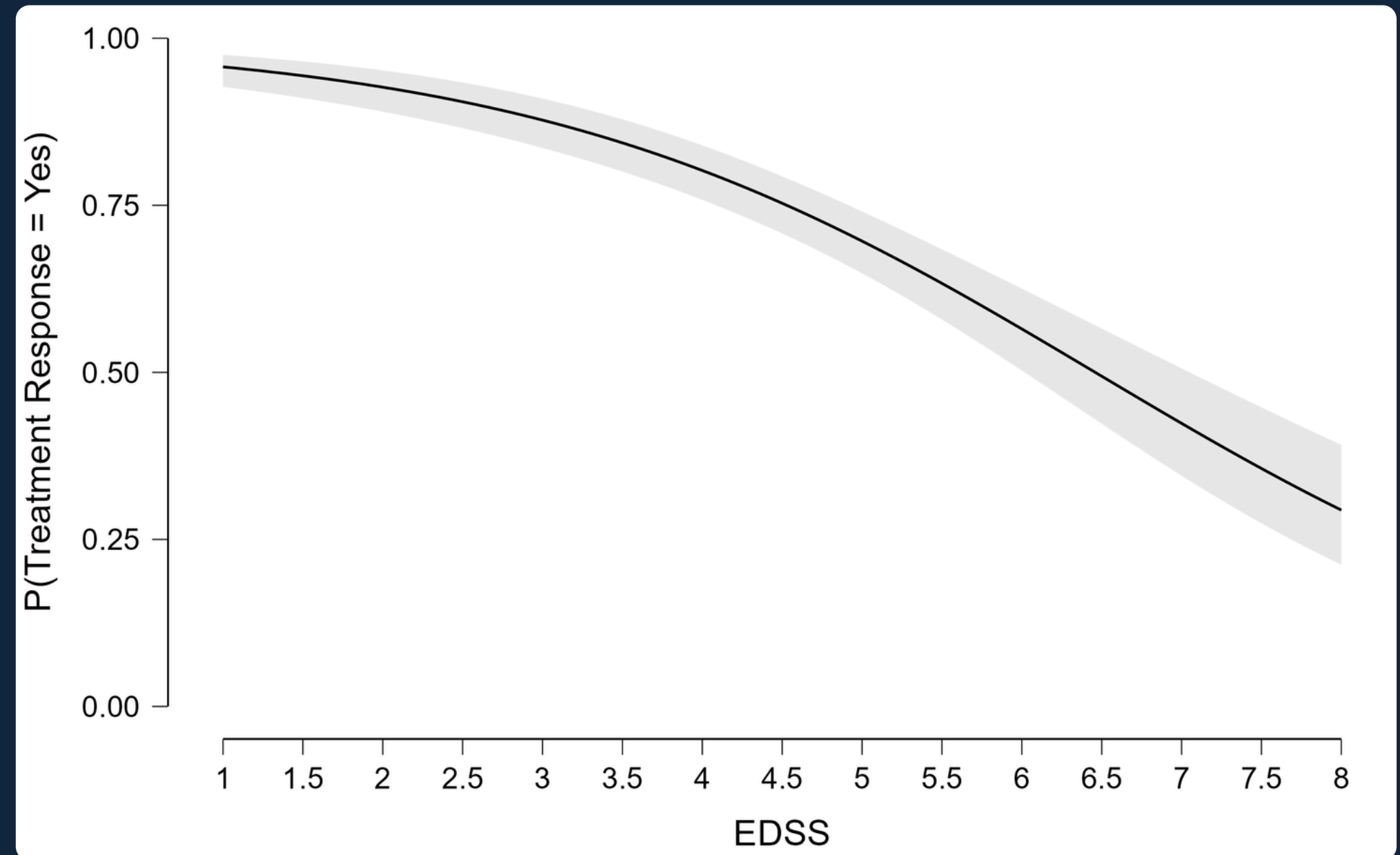
Model predictions error is around ± 1.4 (RMSE)

EDSS and Response to Treatments

Mann-Whitney : $p < 0.001$

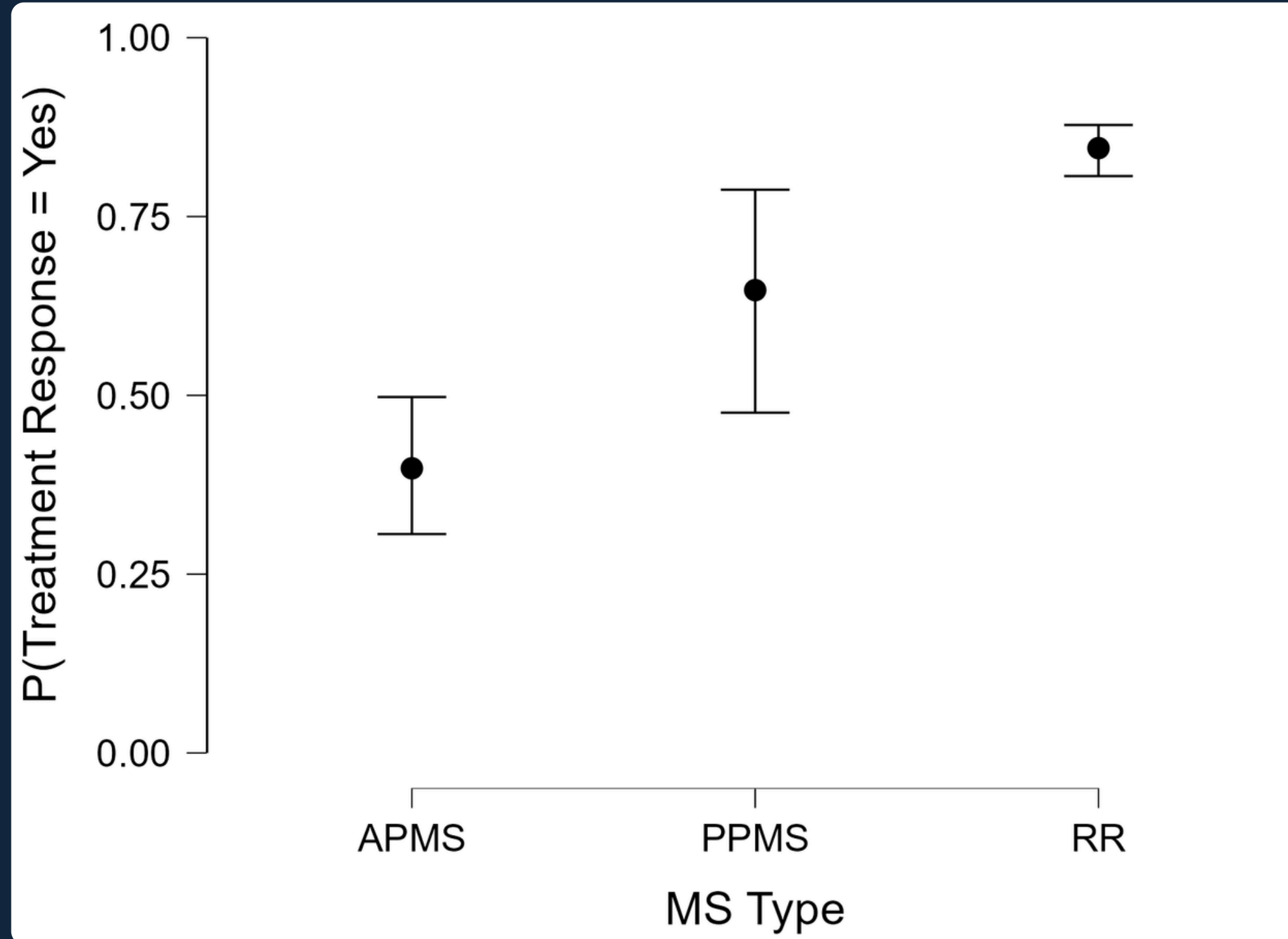


Logistic Regression (CI=95%)



Response to Treatments by MS Type

Logistic Regression (CI=95%)



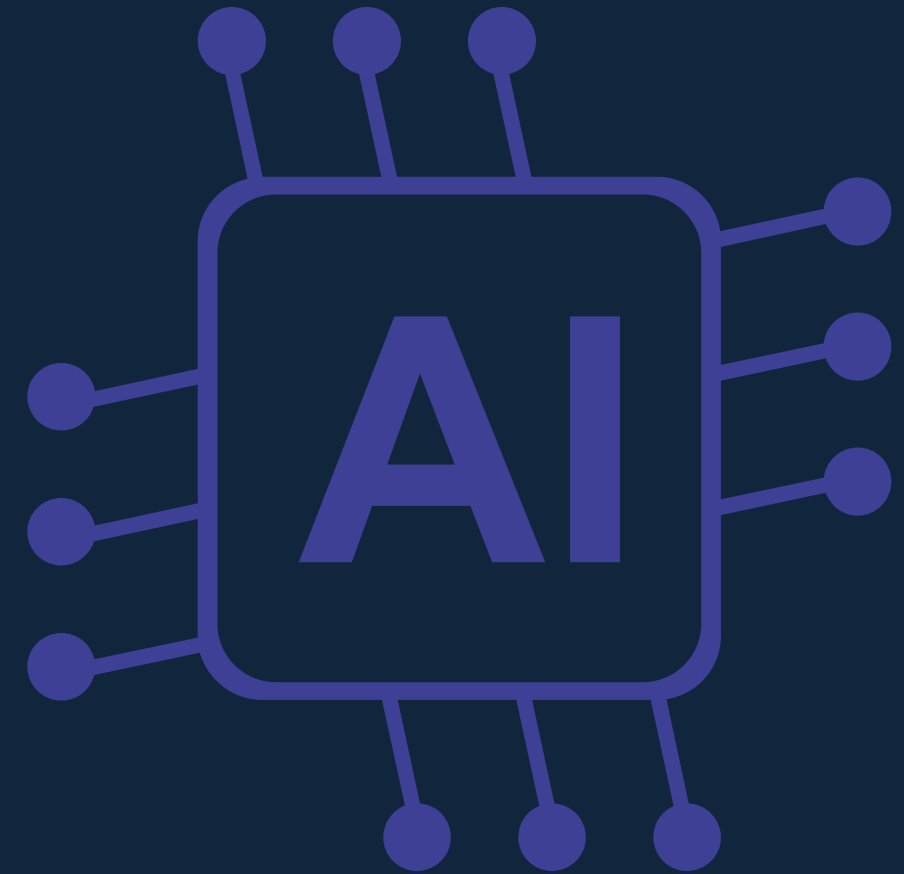
Using Machine Learning to Predict Effective Treatments

We aimed to identify the best treatment combinations for patients using machine learning models.

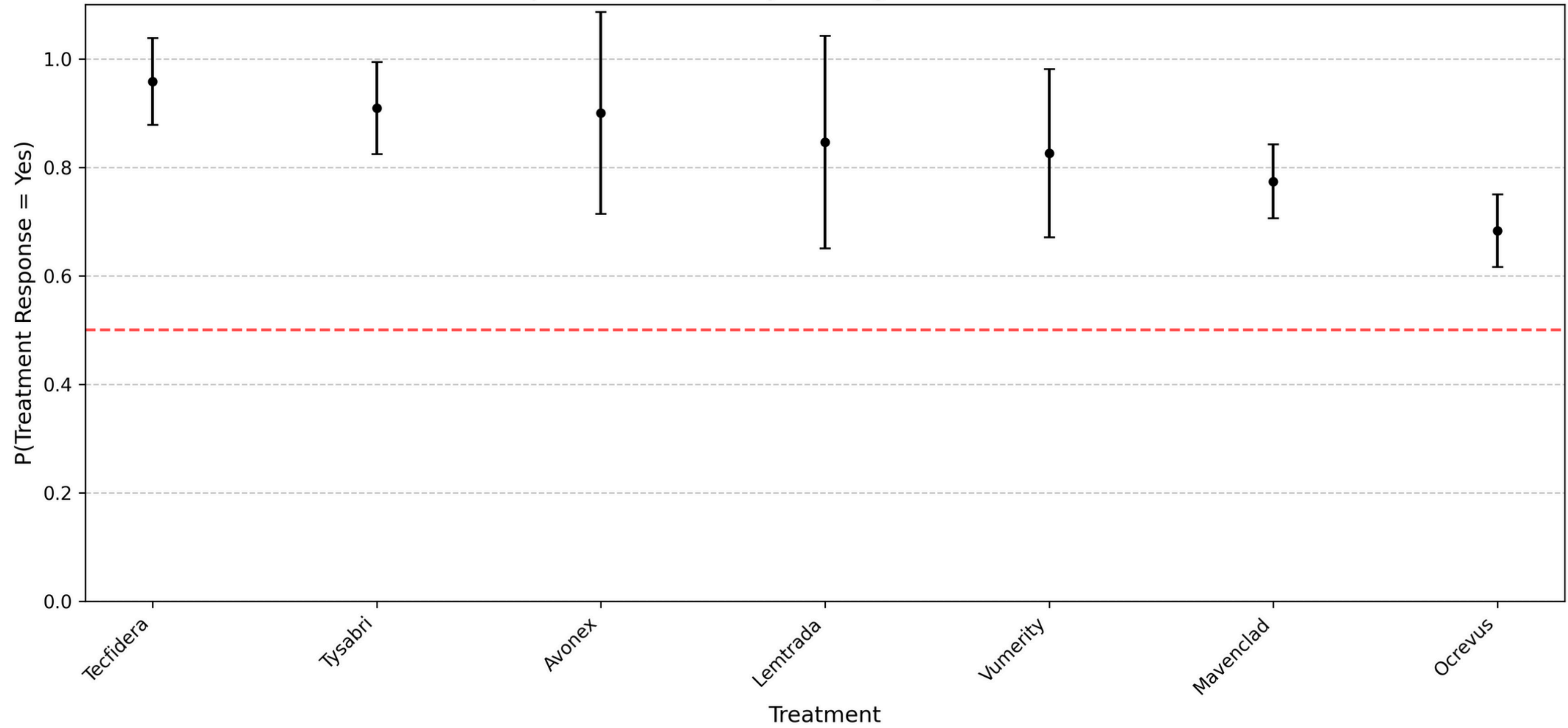
The Decision Tree classifier model was the best, with F1 score of 0.72 due to the task low complexity, which help to identify significant treatment combinations with high interpretability.

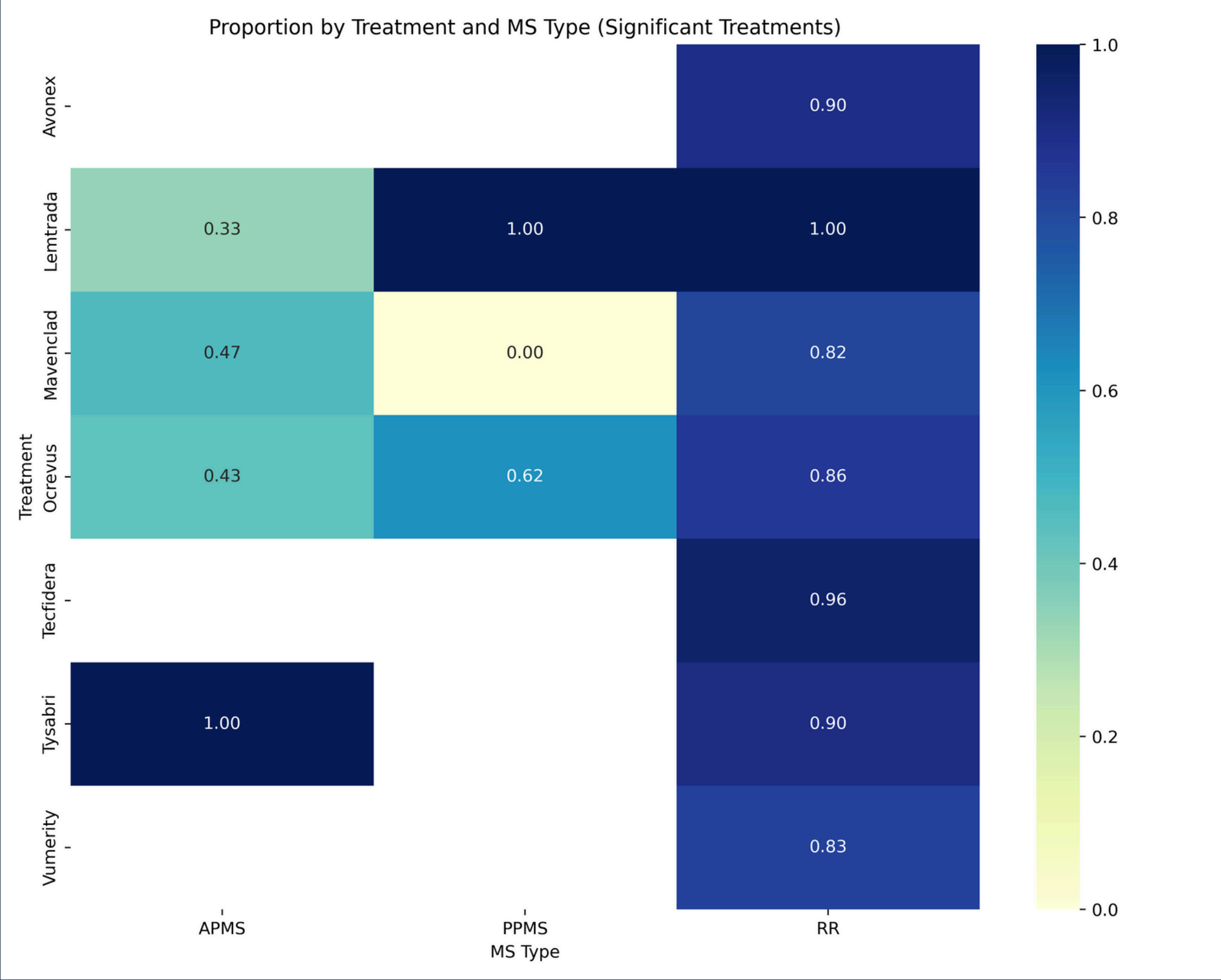
Models Tested:

1. Decision Tree
 2. Gradient Boosting
 3. Random Forest
 4. Support Vector Machine
 5. K-Nearest Neighbors
- Due to small sample size for some treatments our predictions reliability is limited.

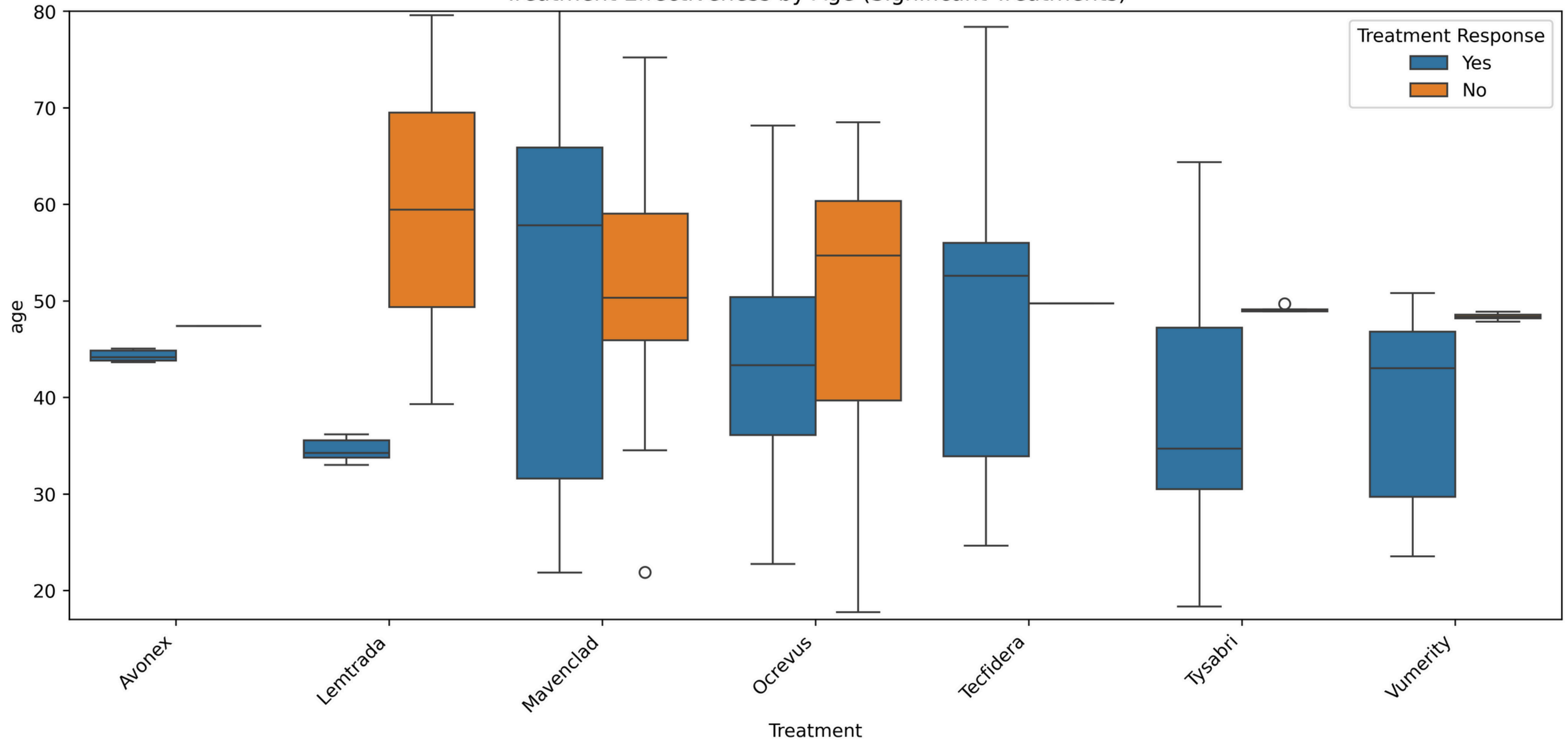


Response Probability for Significant Treatments

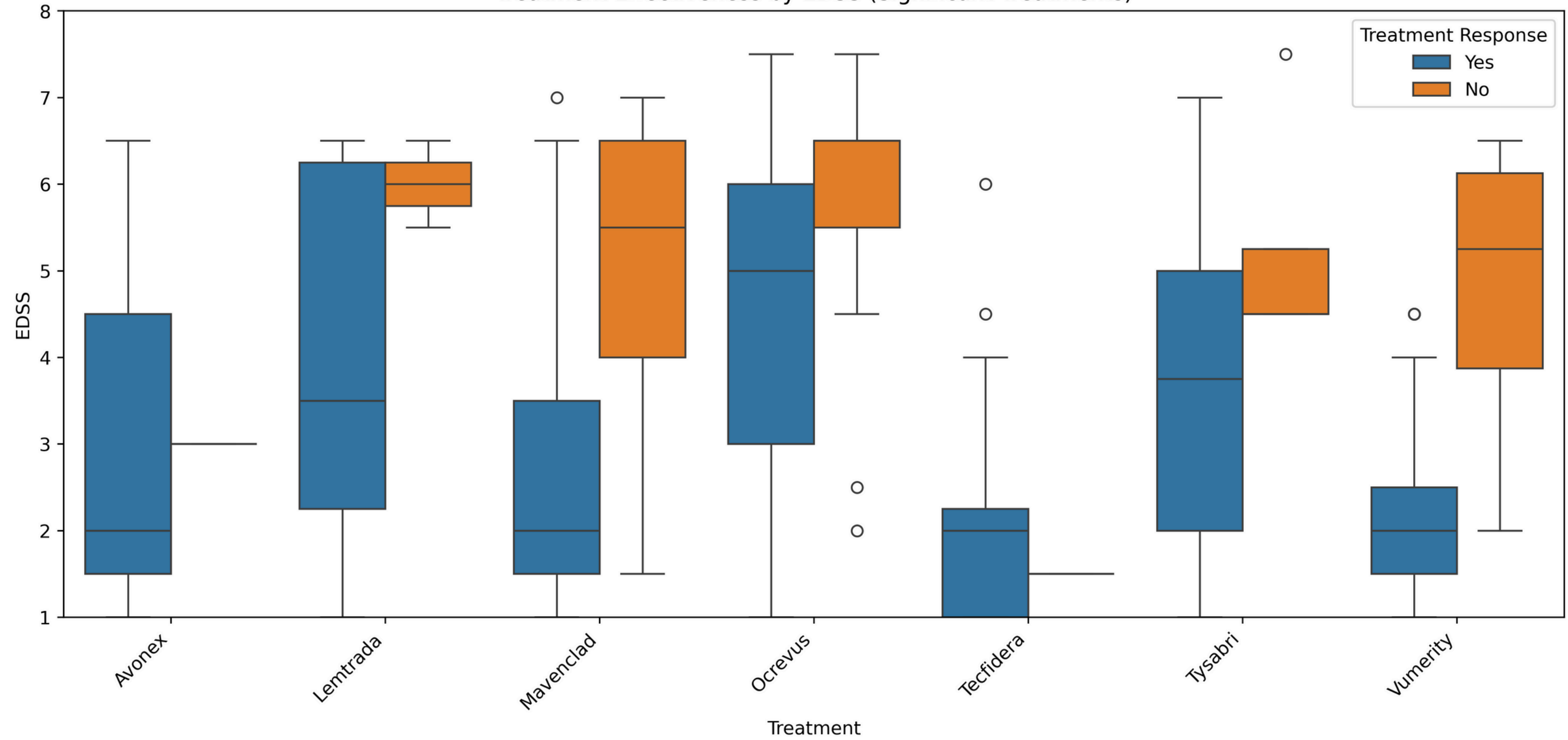


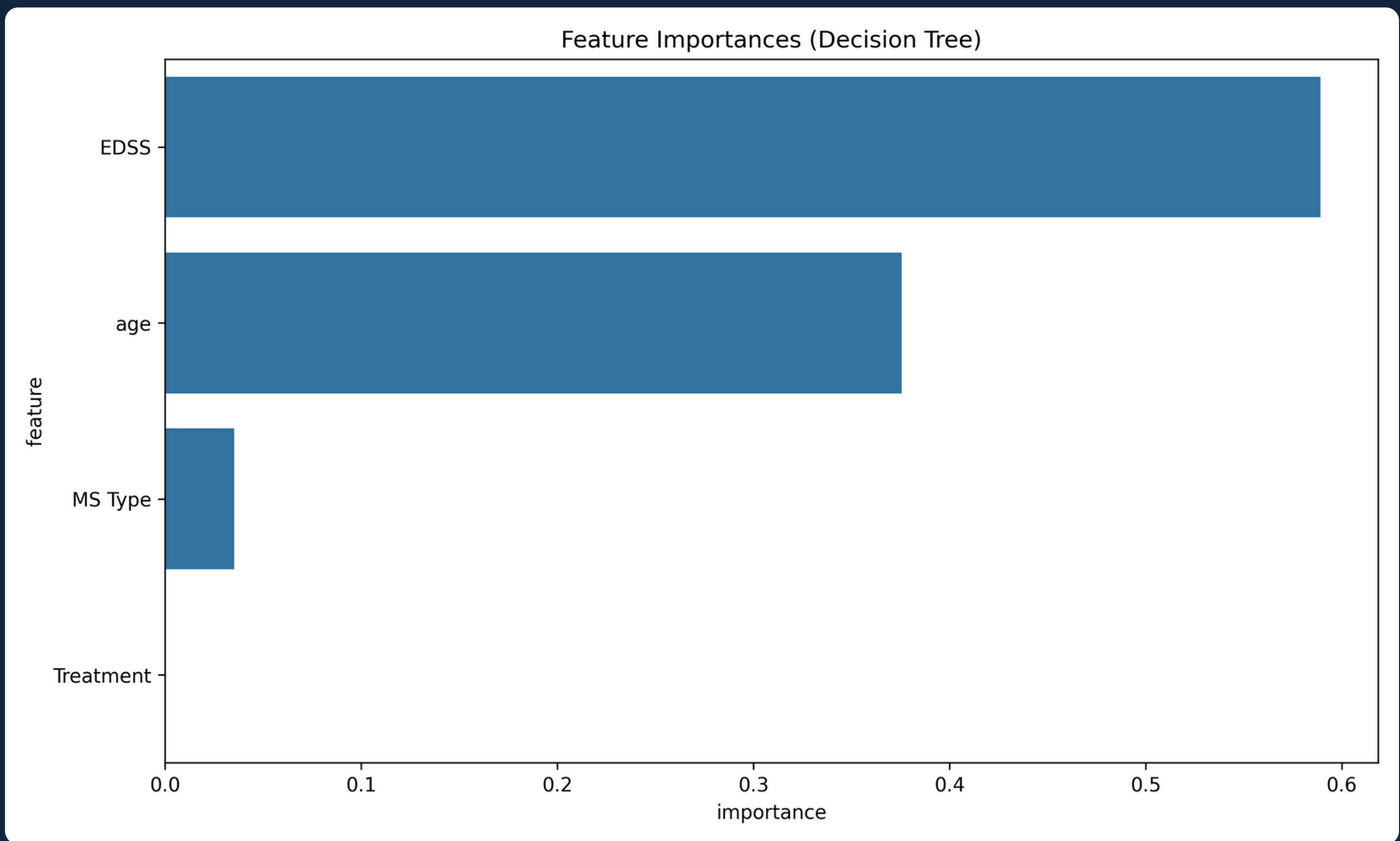


Treatment Effectiveness by Age (Significant Treatments)



Treatment Effectiveness by EDSS (Significant Treatments)





Best Treatment Effectivness Combinations

Treatment	Patients	MS-Type	Proportion	Age	EDSS	p-value
Avonex	10	RR	90.00%	43.8 to 45.4	1.6 to 4.5	0.0215
Lemtrada	13	RR	84.62%	30.8 to 45.9	3.0 to 5.5	0.0225
Mavenclad	146	RR	77.40%	50.2 to 55.6	3.0 to 3.7	<0.001
Ocrevus	186	RR	68.28%	44.1 to 47.6	4.8 to 5.3	<0.001
Tecfidera	24	RR	95.83%	40.6 to 52.7	1.5 to 2.6	<0.001
Tysabri	44	RR	90.91%	36.0 to 43.2	3.0 to 4.1	<0.001
Vumerity	23	RR	82.61%	37.1 to 45.0	2.0 to 3.4	0.0026

Model Evaluation

Cross-validation with 6 folds

Decision Tree Classification Report:

	precision	recall	f1-score	support
No	0.41	0.31	0.35	104
Yes	0.80	0.87	0.83	342
accuracy			0.74	446
macro avg	0.61	0.59	0.59	446
weighted avg	0.71	0.74	0.72	446

- Poor results for predicting No Response to Treatments due to small sample size.