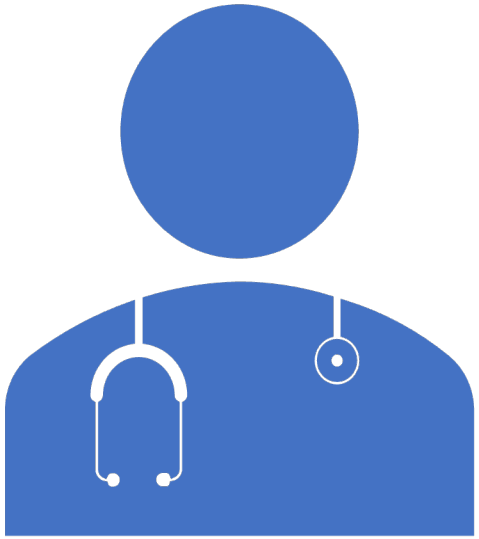
Prediction modeling for HTA using Explainable AI (XAI)

Gunjan Chandra,
BISG, University of Oulu

Goal



Create a Clinical Decision Support System (CDSS) to support clinicians make better decisions

- **XAI ensures that the system's recommendations are understandable and can be explained.**
- **Addressing challenges associated with the complexity and interpretability of AI-driven clinical decision-making.**

Predicting clinical outcomes

Clinical Epidemiology

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ORIGINAL RESEARCH

Data-Driven Identification of Long-Term Glycemia Clusters and Their Individualized Predictors in Finnish Patients with Type 2 Diabetes

Piia Lavikainen[1,*], Gunjan Chandra[2,*], Pekka Siirtola[2], Satu Tamminen[2], Anusha T Ihalapathirana[2], Juha Röning[2], Tiina Laatikainen[3–5], Janne Martikainen[1]

[1]School of Pharmacy, University of Eastern Finland, Kuopio, Finland; [2]Biomimetics and Intelligent Systems Group, Faculty of ITEE, University of Oulu, Oulu, Finland; [3]Joint Municipal Authority for North Karelia Social and Health Services (Siun Sote), Joensuu, Finland; [4]Department of Public Health and Social Welfare, Finnish Institute for Health and Welfare, Helsinki, Finland; [5]Institute of Public Health and Clinical Nutrition, University of Eastern Finland, Kuopio, Finland

Objectives:

- Identify patients with homogeneous long-term HbA1c trajectories.
- Predict trajectory membership using explainable machine learning and various predictors (clinical, treatment, socio-economic).

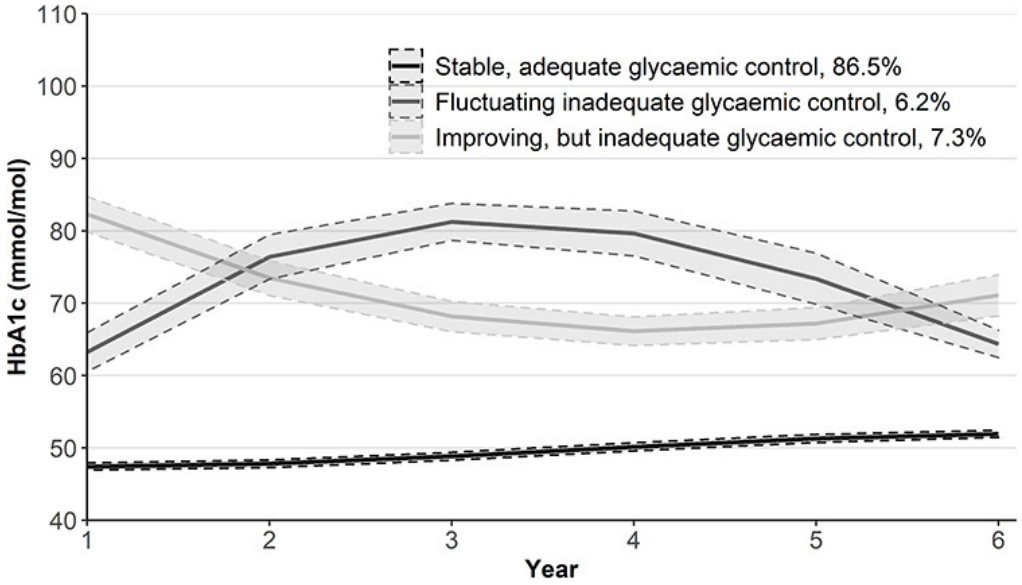


Figure 1. Estimated HbA1c trajectories.

 This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement № 825162.

Results

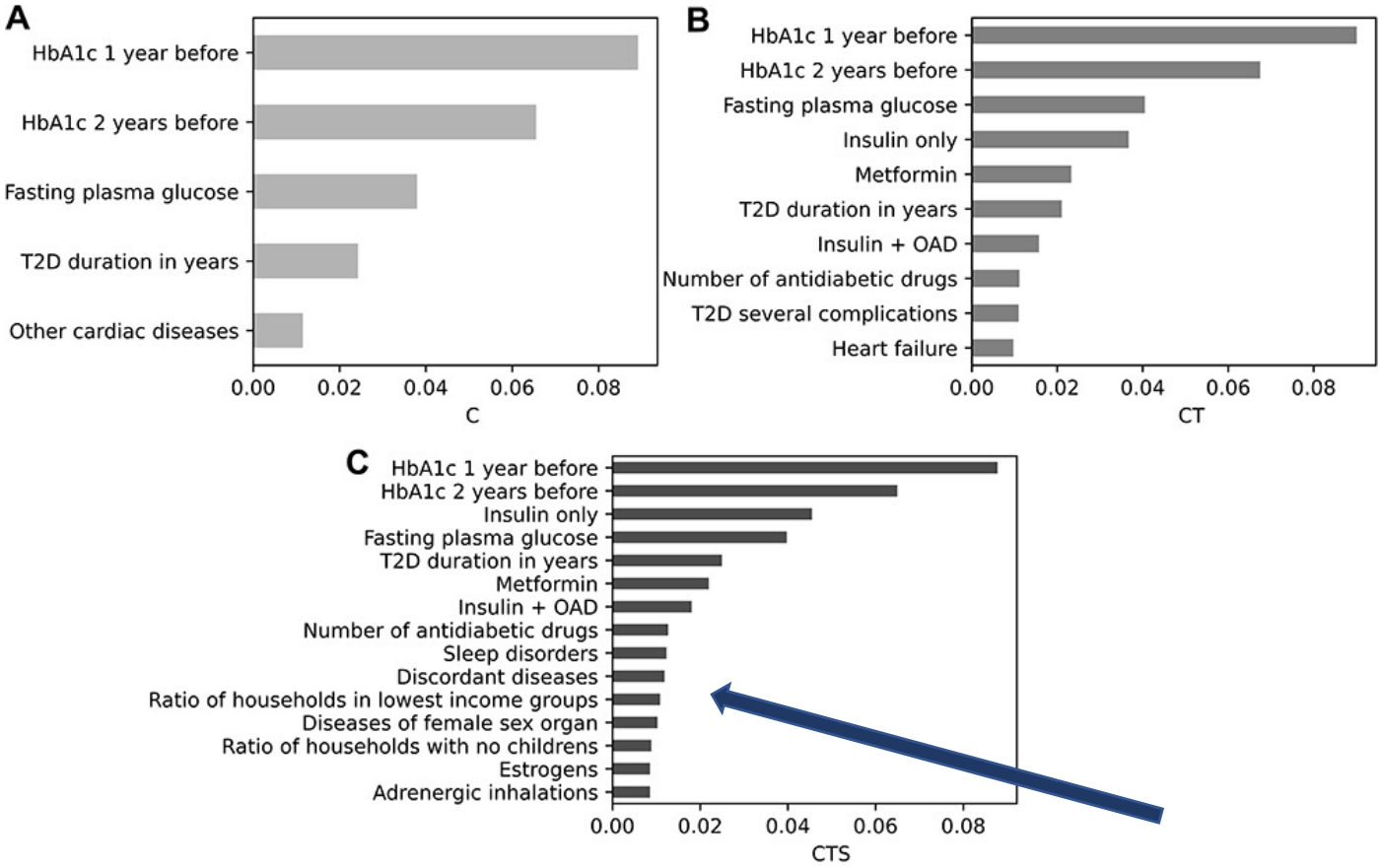


Figure 2. Feature importance plot for (**A**) Clinical (C), (**B**) Clinical + Treatment (CT), (**C**) and Clinical + Treatment + SES (CTS) models.

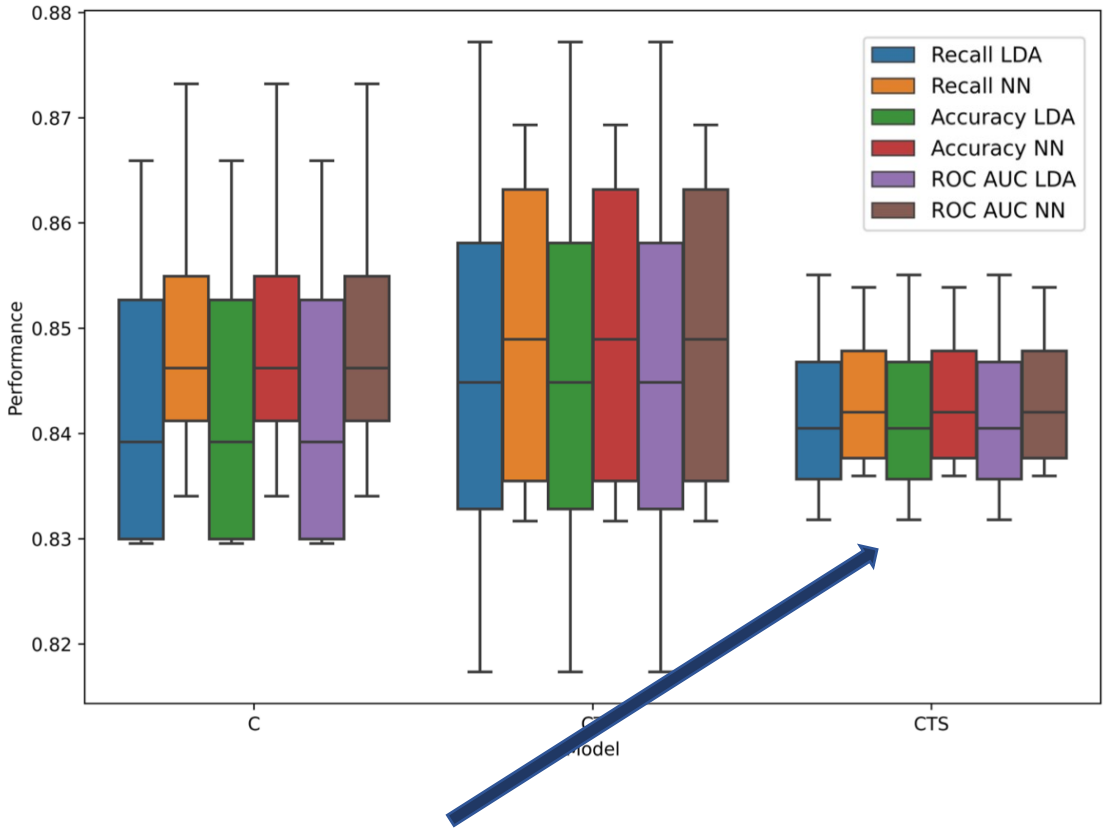


Figure 3. Performance of models over different splits in 4-fold cross-validation.

Global and local explaination (SHAP)

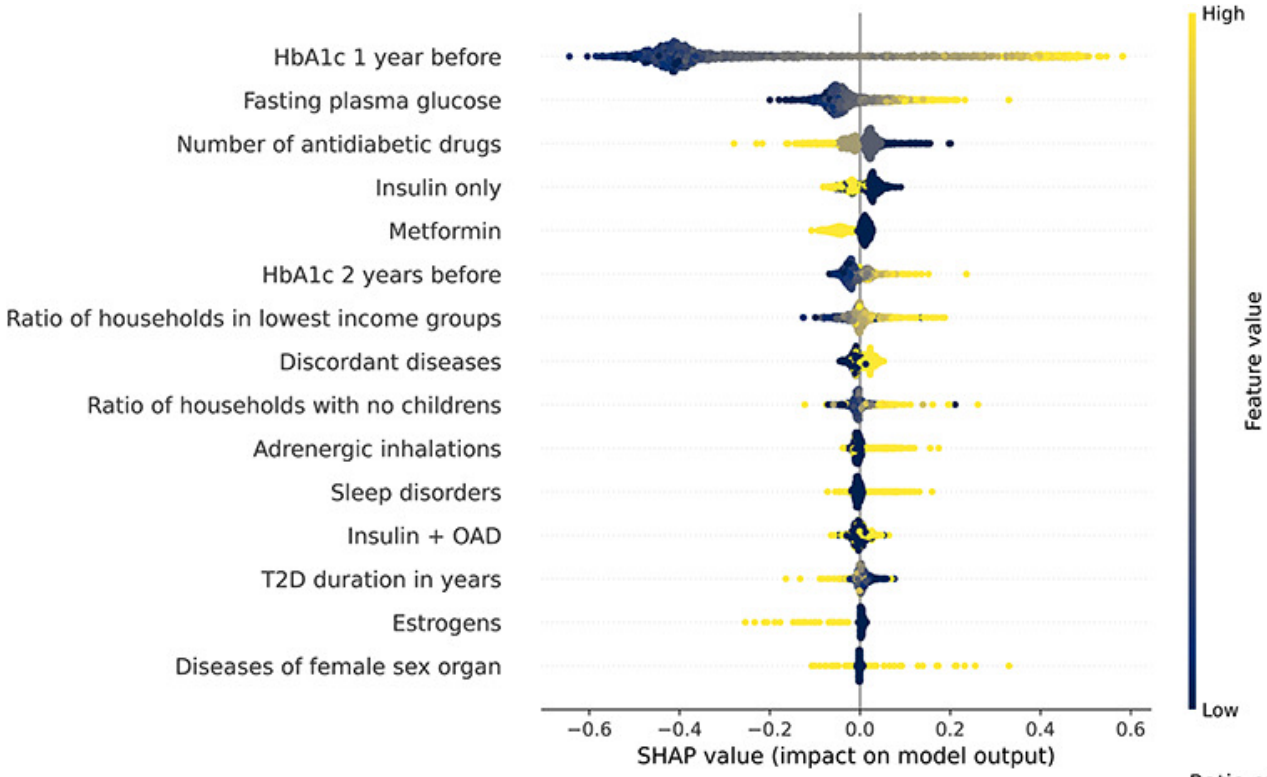
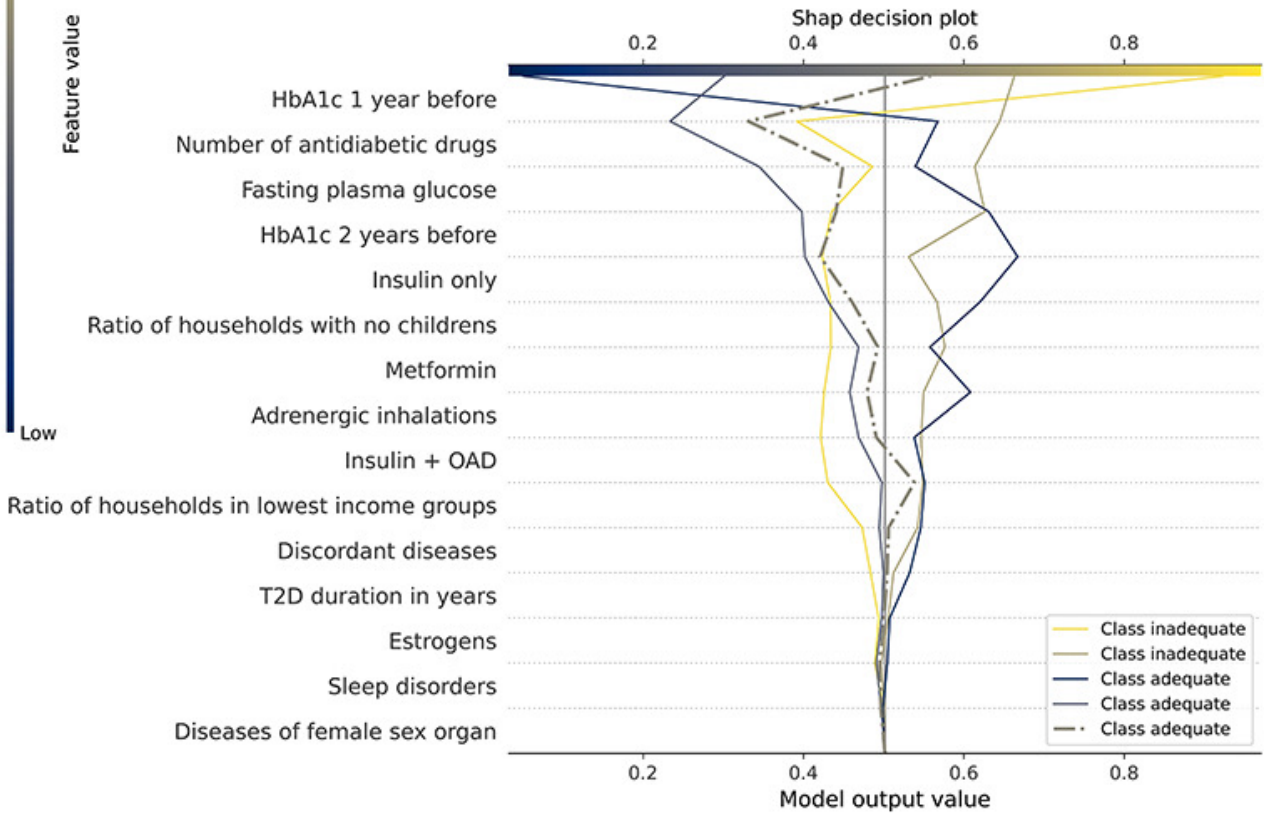


Figure 4. SHAP summary plot

Figure 5. SHAP decision plot of five samples



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Explainable Artificial Intelligence to predict clinical outcomes in type 1 diabetes and relapsing-remitting multiple sclerosis adult patients

Anusha Ihalapathirana [a,*], Konstantina Chalkou [b], Pekka Siirtola [a], Satu Tamminen [a], Gunjan Chandra [a], Pascal Benkert [c], Jens Kuhle [d,e], Georgia Salanti [b], Juha Röning [a]

[a] Biomimetics and Intelligent Systems Group, Faculty of Information Technology and Electrical Engineering, University of Oulu, Oulu, FI-90014, Finland
[b] Institute of Social and Preventive Medicine, University of Bern, Bern, CH-3012, Switzerland
[c] Clinical Trial Unit, Department of Clinical Research, University Hospital Basel, University of Basel, Basel, 4001, Switzerland
[d] Multiple Sclerosis Centre, Neurologic Clinic and Policlinic, Departments of Head, Spine and Neuromedicine, Biomedicine and Clinical Research, University Hospital Basel and University of Basel, Basel, 4001, Switzerland
[e] Research Center for Clinical Neuroimmunology and Neuroscience (RC2NB), University Hospital and University of Basel, Basel, 4001, Switzerland

Objectives:

Predict clinical outcomes in type 1 diabetes and relapsing-remitting multiple sclerosis adult patients

Compare machine learning and statistical methods

 This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement № 825162.

Results

Outcome	Models built using statistically identified prognostic / risk factors	Models built using features selected through ML methods	Statistical model
Relapses (MS)	AUC – 0,67 BA – 0,66 F1 score – 0,71	Male AUC – 0,70 BA – 0,70 F1 score – 0,84	AUC – 0,65
		Female AUC – 0,69 BA – 0,68 F1 score – 0,76	
Severe hypoglycemia (T1D)	AUC – 0.65 BA – 0,66 F1 score – 0,65	Male AUC – 0,88 BA – 0,85 F1 score – 0,84	-
		Female AUC – 0,82 BA – 0,79 F1 score – 0,84	
Diabetic Ketoacidosis (T1D)	AUC – 0,69 BA – 0,68 F1 score – 0,78	AUC – 0,85 BA – 0,83 F1 score – 0,78	-

- Machine learning models that rely only on known risk factors yield moderate prediction accuracy.
- Feature selection methods have the potential to improve the prediction of medical outcomes.
- Socioeconomic factors, physical health, and mental health impact the prediction of medical outcomes.

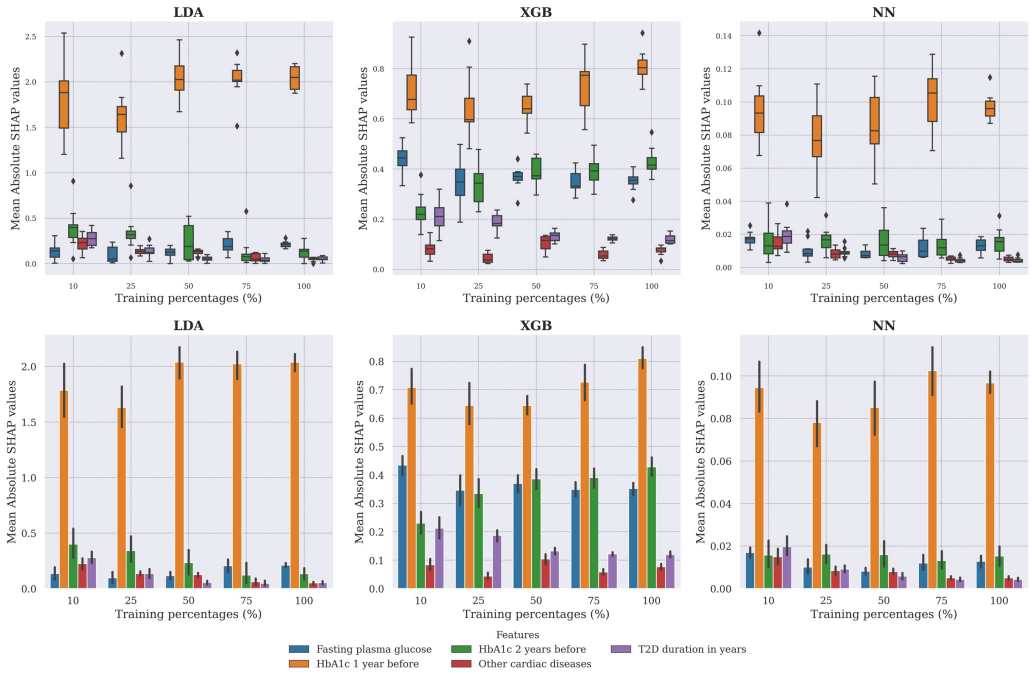
Objective: Influence of Data Size and Class Balance on Machine Learning Classification Performance and SHAP explanations

Next Generation Health Technology Assessment

Results:

- Various machine learning models work best with different amounts of training data, and the effect of imbalanced data on performance depends on the metrics used.

- SHAP explanations are more effective when there is balanced background data, and their stability improves with larger background datasets.

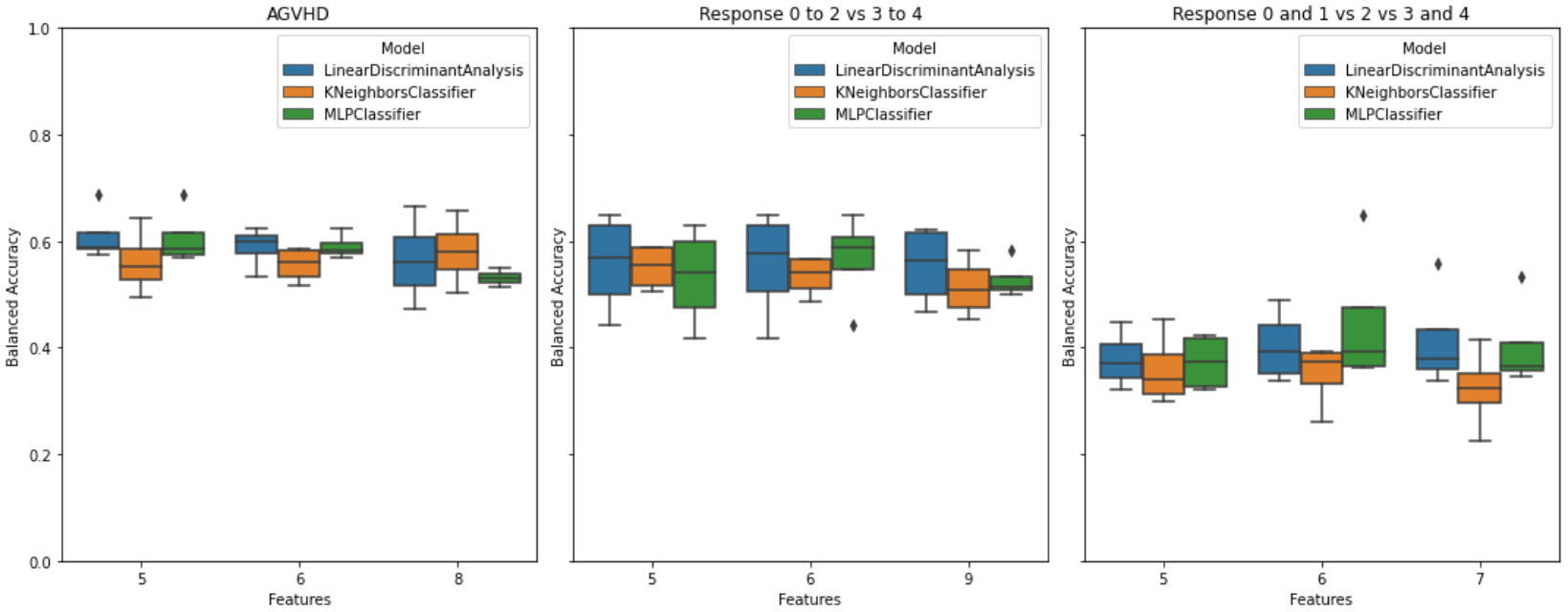


Orphan diseases

Objective: AI for Predicting Acute Graft versus-Host Disease and Subtypes in Allogeneic Hematopoietic Cell Transplantation for T-cell Prolymphocytic Leukaemia

Methods:

- Open data set from Centre for International Bone and Marrow Transplant Research (CIBMTR)
- Only predefined prognostic features were used



Results:

- Models predict the occurance of aGVHD and its sub-types with moderate to low accuracy.
- The performance of the models could be impacted by the data size or the absence of comprehensive data.

In progress

Predict the success of ESAs in EUMDS patients and time to response.

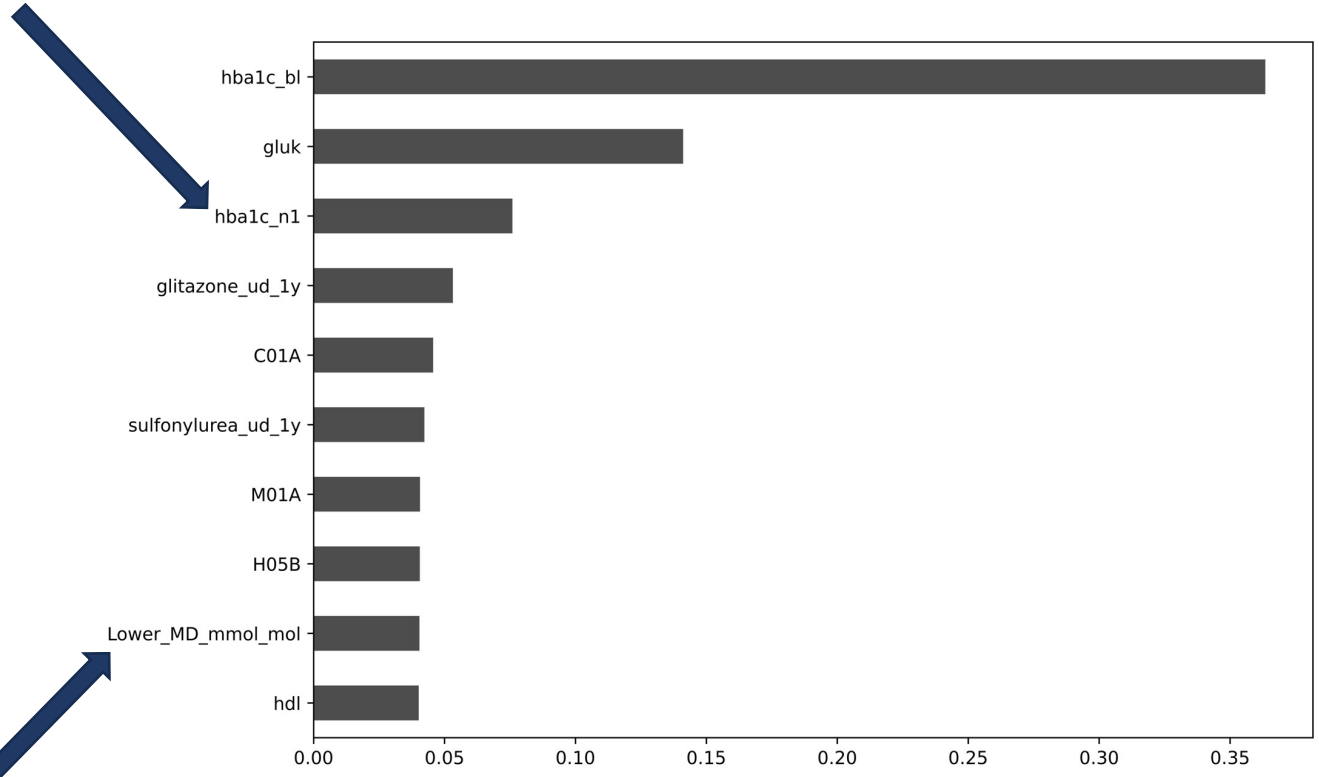
Investigating ITE using Causal ML with Time-to-Event Data in AML Patients Undergoing Allo-HCT with Different Treatment Regimens.

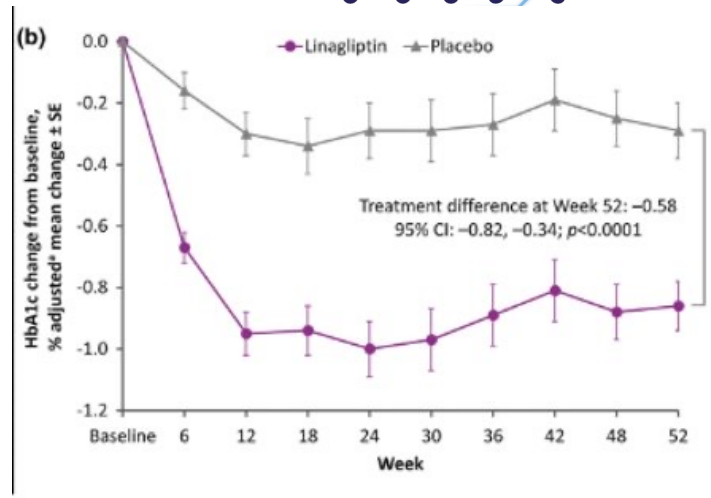
Predicting treatment outcomes

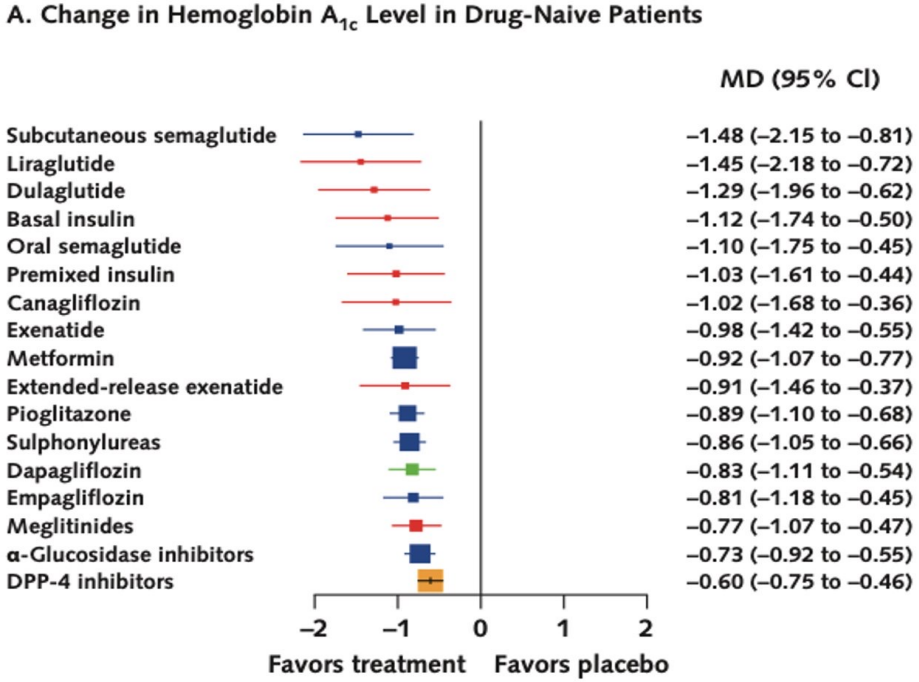
Offset model

Objective: Predicting Change in HbA1c Values Following Initiation of Antidiabetic Drugs in Type 2 Diabetes using XAI

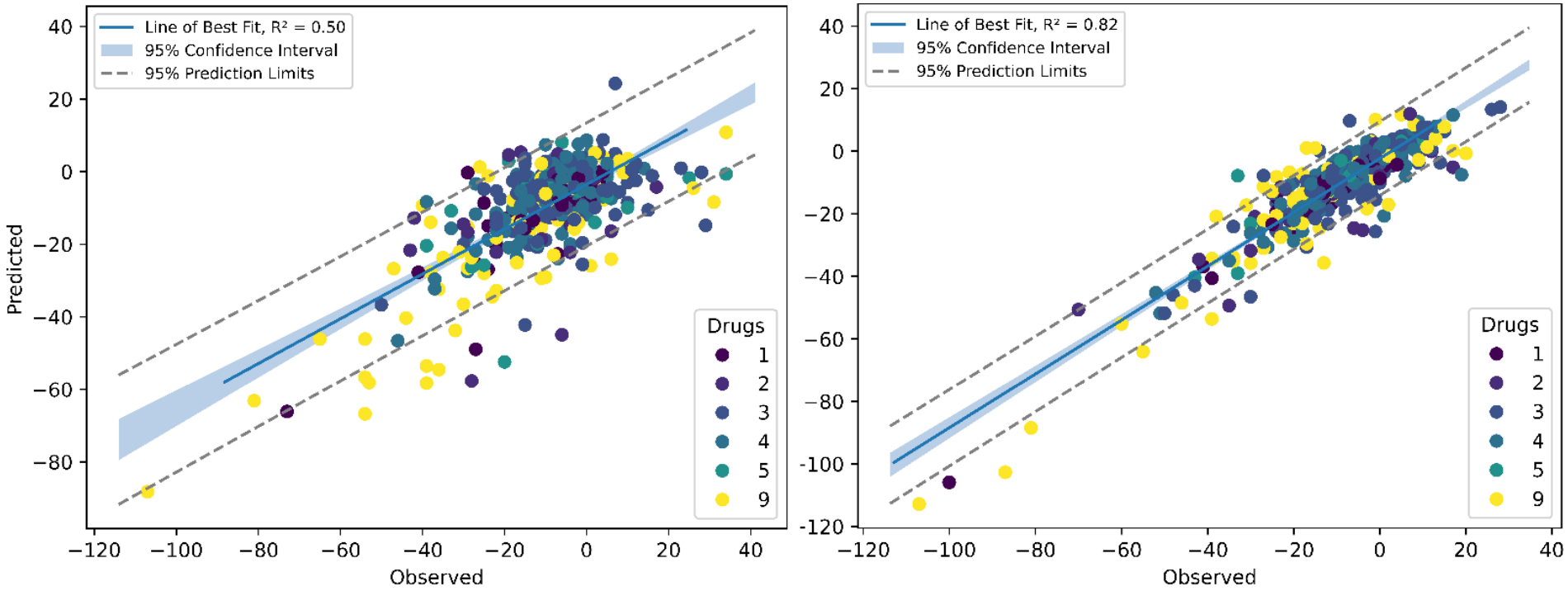
- **Distance from baseline to target:** Minimum: 80, Median: 280.0, Maximum: 364
- Added expected HbA1c changes from RCT as predictors.
- Added HbA1c follow up value.







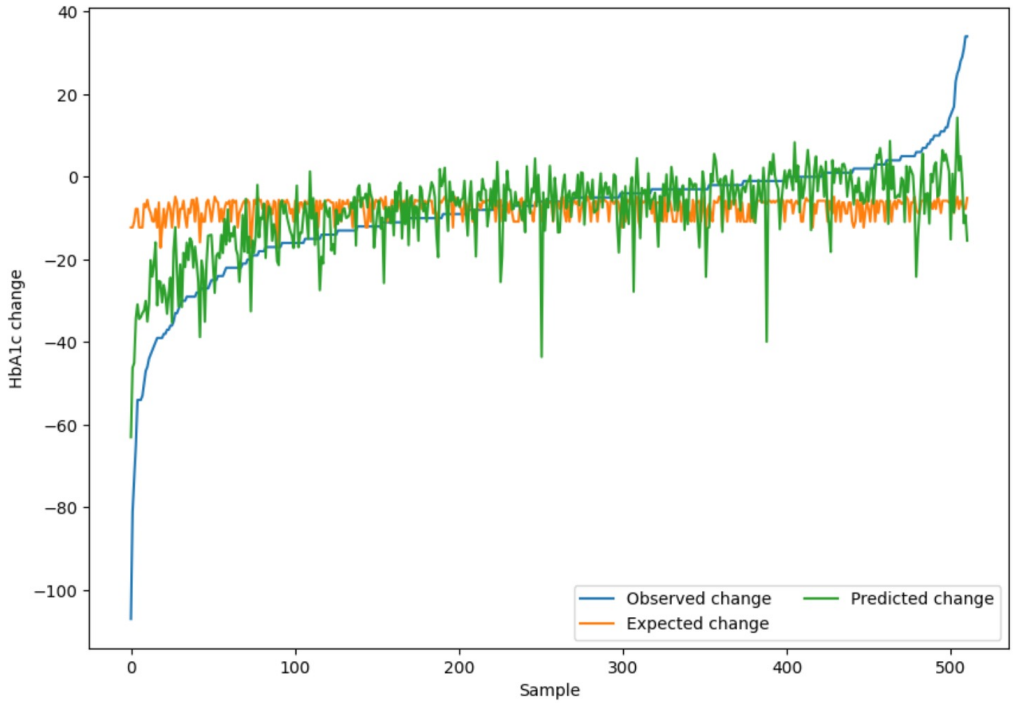
Results



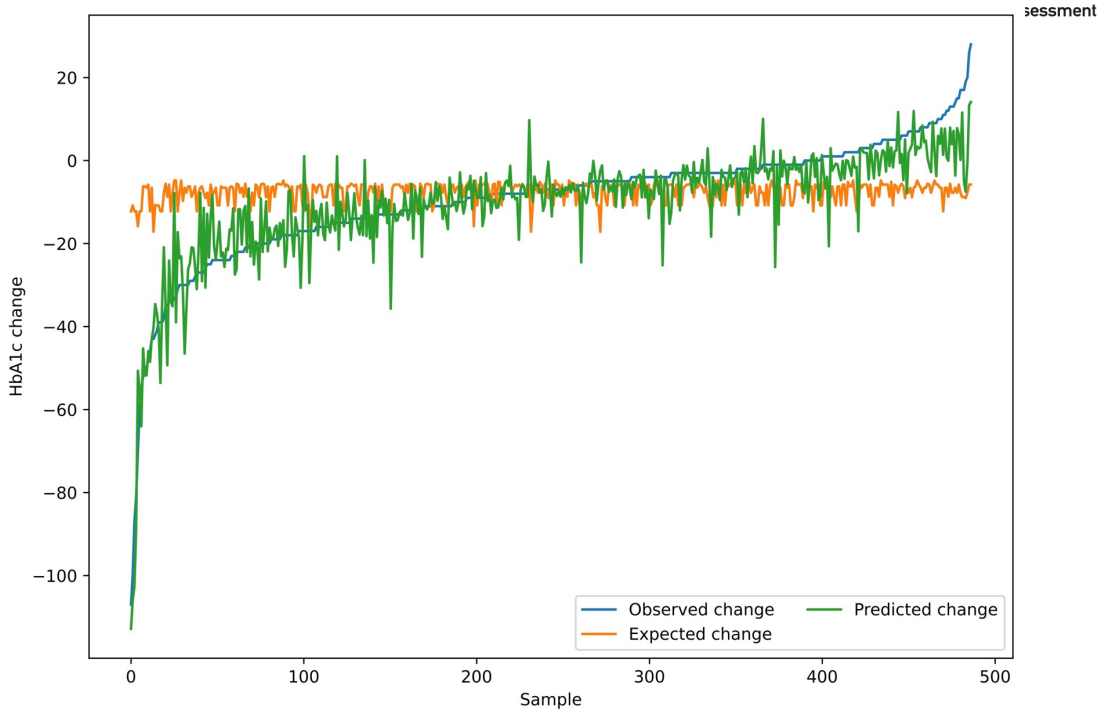
Code	Name
1	Metformin
2	GLP-1 analogues
3	DPP-4 inhibitors
4	SGLT2 inhibitors
5	Combinations of oral blood glucose lowering drugs
9	Insulin

Figure 1. Performance of MLPRegressor Model: Fitted Regression Line for HbA1c Change Before and After Drug Initiation. Base model on the left and model using follow-up HbA1c value after drug initiation on the right.

Results



Base model: AI predicted better in 287 cases, RCT 223 cases



Follow-up HbA1c value: AI predicted better in 290 cases, RCT 196 cases

- AI outperforms RCT values in predicting individualized treatment responses in both cases.
- The occurrence of positive changes following drug initiation raises questions.

Next steps

Multi-target regression modeling for tretament effect calculation and optimal treatment selection.

XAI-based clinical decision support system (Demo-CDSS)

HTx Project

HTx Home Doctor's Interface Admin Search Search

Welcome to HTx Website!

Please select a disease to study from the dropdown menu: Disease

Please select a model to study the disease from the menu: Model

Conclusion

- When employing more holistic modelling approaches, AI demonstrates heightened efficacy in predicting both clinical and treatment outcomes.
- The magnitude of the dataset significantly influences both the performance and explainability of the model.
- Artificial intelligence exhibits the potential to enhance predictive performance specifically for orphan diseases.

Thank you!