Empowering Clinicians to Manage Chronic-comorbid Conditions by Predicting Adverse Outcomes with Transparent AI at the Point of Care

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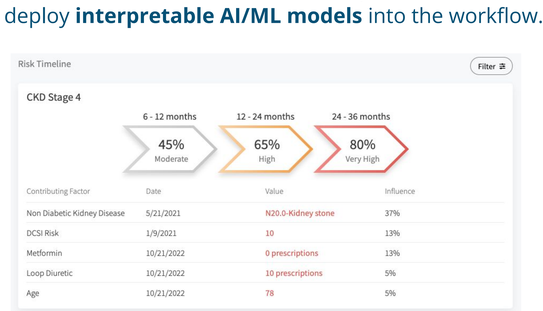
Challenge

The interconnectivity of factors contributing to adverse outcomes (AOs) in type 2 diabetes (T2D) makes it difficult to predict when complications will occur for individual patients. While population stratification of T2D AOs has been studied[1,2,5,6,7,8], **predicting when a specific patient will experience explicit outcomes and deploying person-specific interventions to address those outcomes have not been integrated into clinical workflows.**

Objective

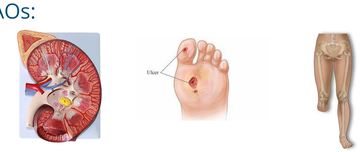
Zephyr AI™ and MedStar Health® have partnered to develop and deploy **interpretable AI/ML models** into the workflow.



Patient AO predictions for 0-5 years are returned as probability measures with individualized contributing factors to **assist clinicians in the delay or prevention of AOs.**

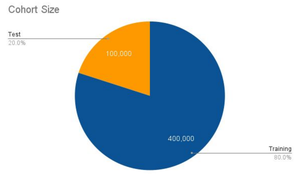
Data

Prioritized* AOs:

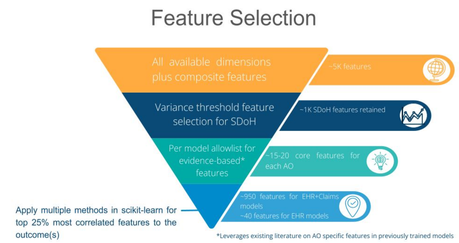


- End Stage Chronic Kidney Disease (ESKD)-CKD 4, CKD 5, and Dialysis
- Acute and Chronic Diabetic foot ulcer (DFU)
- Lower Extremity Amputation (LEA)

A de-identified nationally representative cohort of **1M T2D patients' EHR and claims are joined with the AHRQ SDoH database[4]**.



The training set comprises ~400k patients with ~5 years of depth. Another ~100k patients are held out for testing.



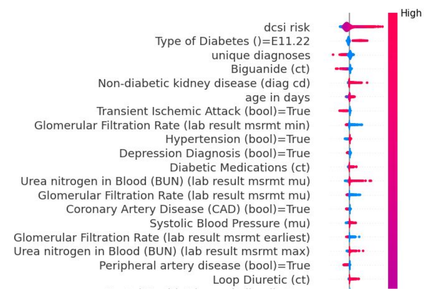
We compute ~5k features and **use the highest quality ~1k features** in training. Feature provenance is tracked to enable smart imputation when limited patient data is available.

Methods

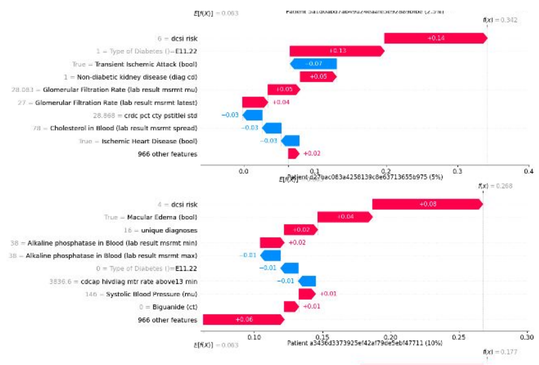
Multiple types of survival models (RSF, AFT, MTLR, PLSR, CCA) are trained for each AO from first interaction to the date of T2D diagnosis plus a fixed observation period (6 or 12 months). We have generally obtained the best performance, in metrics and scalability, from MTLR.

*considered clinically relevant and actionable

Stratification of a homogenous cohort with **explainability is achieved using SHapley Additive exPlanations (SHAP)**[11] and aids in establishing model trust.



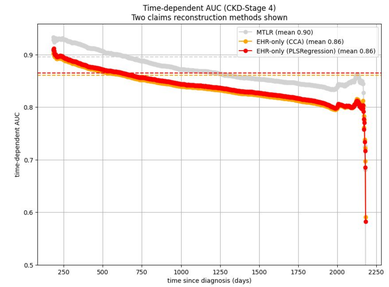
A SHAP "waterfall plot" **shows the 10 most influential features for a given patient.** SHAP values are additive, their sum gives the individual risk vs. population prevalence of an adverse outcome within in the prediction window. Feature-level contributions to risk are critical to clinicians' interpretation of models[12,13] and prioritization of interventions.



Results

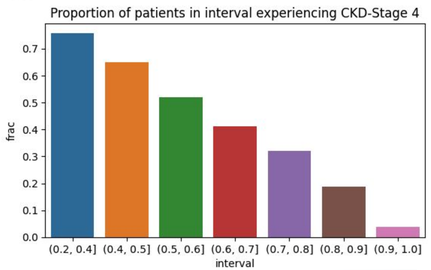
AO	Lit. AUC	Zephyr AUC
ESKD	0.81[5]-0.84[6]	0.80-0.93
DFU	0.86[7]-0.88[8]	0.78-0.86
LEA	0.72[9] -0.84[10]	0.83-0.88

Most models compare favorably to metrics published in the space[14, 18, 19, 20] and show an **average AUC of 0.85, concordance indices > 0.76, and Brier scores < 0.07 across the AOs.**



Matrix reconstruction techniques allow use of partial patient data at a modest cost in AUC.

Backtesting: **the proportion of patients experiencing a given adverse outcome correlates with the predicted risk.**



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ZEPHYR AI

Evaluating predictive capability, generalizability and clinical utility of Zephyr models on 300K T2D MedStar patients is underway