

Supplemental Material

Supplemental Methods: Bootstrap method for decision tree classification

A case-control design was used at the level of follow-up period, allowing for case-crossover for patients with an ischemic stroke. Our dependent variable, a follow-up period with stroke, was compared with all other follow-up periods for patient cases and controls, resulting in an extremely rare event rate of 0.036%. To balance the data, ischemic stroke events were oversampled by labeling the five days prior to an occurrence. Control follow-ups were then randomly undersampled to match the number of oversampled follow-up cases. For patients who experienced an ischemic stroke, follow-up ended on the day prior to the occurrence to prevent the use of device measurements taken on the same day but after the stroke event happened, a situation that would introduce *look ahead* bias into the modeling. Thus, our goal was to accurately predict stroke five days in advance using all labeled follow-up cases and a random sample of follow-up controls.

A recursive partitioning and regression tree algorithm (RPART)^{25, 26} was used to predict which follow-up days had an occurrence of ischemic stroke using baseline characteristics, CHA₂DS₂-VASc score, device parameters, and moving average offsets (SMA_a minus SMA_b) as predictors. Although over/undersampling methods are well documented for managing imbalanced data^{27, 28}, including the prediction for incident AF²⁹, we recognized the oversampling bias in our design and used a bootstrapping routine with 1,000 repetitions to remove the bias and improve classifier accuracy. For each bootstrap iteration:

1. Patients were randomly partitioned into training (70%) and validation (30%) sets.

2. Follow-up controls were randomly sampled without replacement to equal the number of follow-up cases, resulting in a balanced training set.
3. An exhaustive classification tree with a minimum terminal node size equal to 80, a maximum depth equal to 8, and a complexity parameter equal to 0 was fit to the balanced training set.
4. The misclassification rate for each subtree in Step 3 was calculated using 10-fold cross validation. The exhaustive tree was then pruned back to the subtree with the lowest misclassification rate.
5. Variable importance and split information from the model fit in Step 4 were saved.
6. The unbalanced validation set was classified using the model fit from Step 4.
7. Area under the curve (AUC) and classification statistics from Step 6 were saved.

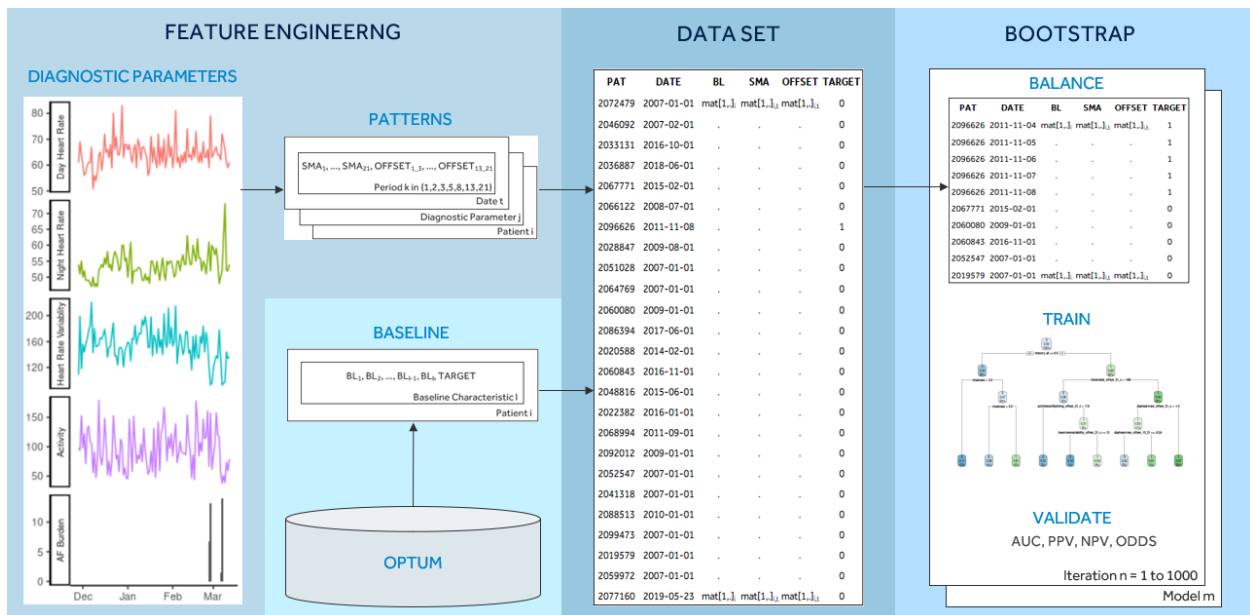


Table S1: Codes used for conditions of interest

Disease	Type	ICD	Codes
Atrial Fibrillation	diag	09	42731
		10	I480, I481, I482, I4891
Heart Failure	diag	09	40201, 40211, 40291, 40401, 40403, 40411, 40413, 40491, 40493, 428*
		10	I110, I130, I132, I50*
Hypertension	diag	09	401*, 402*, 403*, 404*, 405*
		10	I10*, I11*, I12*, I13*, I15*
Stroke/TIA	diag	09	433*, 434*, 435*, 436*, V1254
		10	G450, G451, G452, G458, G459, I163*, I165*, I66*, Z8673
Vascular Disease	diag	09	4400, 4402*, 4439
		10	I700, I702*, I739
Diabetes Mellitus	diag	09	250*0, 250*1, 250*2, 250*3
		10	E10*, E11*
Ischemic Stroke	diag	09	436*, 43301, 43311, 43321, 43331, 43381, 43391, 43401, 43411, 43491, 99702
		10	I636, I638*, I639, I6300, I63011, I63012, I63013, I63019, I6302, I63031, I63032, I63033, I63039, I6309, I6310, I63111, I63112, I63113, I63119, I6312, I63131, I63132, I63133, I63139, I6319, I6320, I63211, I63212, I63213, I63219, I6322, I63231, I63232, I63233, I63239, I6329, I6330, I63311, I63312, I63313, I63319, I63321, I63322, I63323, I63329, I63331, I63332, I63333, I63339, I63341, I63342, I63343, I63349, I6339, I6340, I63411, I63412, I63413, I63419, I63421, I63422, I63423, I63429, I63431, I63432, I63433, I63439, I63441, I63442, I63443, I63449, I6349, I6350, I63511, I63512, I63513, I63519, I63521, I63522, I63523, I63529, I63531, I63532, I63533, I63539, I63541, I63542, I63543, I63549, I6359, I97810, I97811, I97820, I97821
	drg	061, 062, 063	

Disease	Type	ICD	Codes
Systemic Embolism	diag	09	44401, 44409, 4441, 44421, 44422, 44481, 44489, 4449
		10	I7401, I7409, I7410, I7411, I7419, I742, I743, I744, I745, I748, I749
Myocardial Infarction	diag	09	410*, 412*
		10	I21*, I22*, I23*, I252
Sleep Apnea	diag	09	32720, 32721, 32723, 32729
		10	G4730, G4731, G4733, G4739
COPD	diag	09	49121
		10	J441
Coronary Artery Disease	diag	09	41400, 41401
		10	I2510
Chronic Kidney Disease	diag	09	585*
		10	N18*
Valvular Heart Disease	diag	09	394*, 395*, 396*, 397*
		10	I34*, I35*, I37*
Hypothyroidism	diag	09	2449
		10	E039
Hyperthyroidism	diag	09	24290
		10	E0590
Ablation	proc	09	3734, 93650, 93651, 93652, 93653, 93654, 93655, 93656, 93657
		10	02583ZZ

ICD indicates International Classification of Diseases; drg, diagnosis-related group; diag, diagnosis; proc, procedure; TIA, transient ischemic attack; COPD, chronic obstructive pulmonary disease;

Figure S1: Cohort selection diagram.

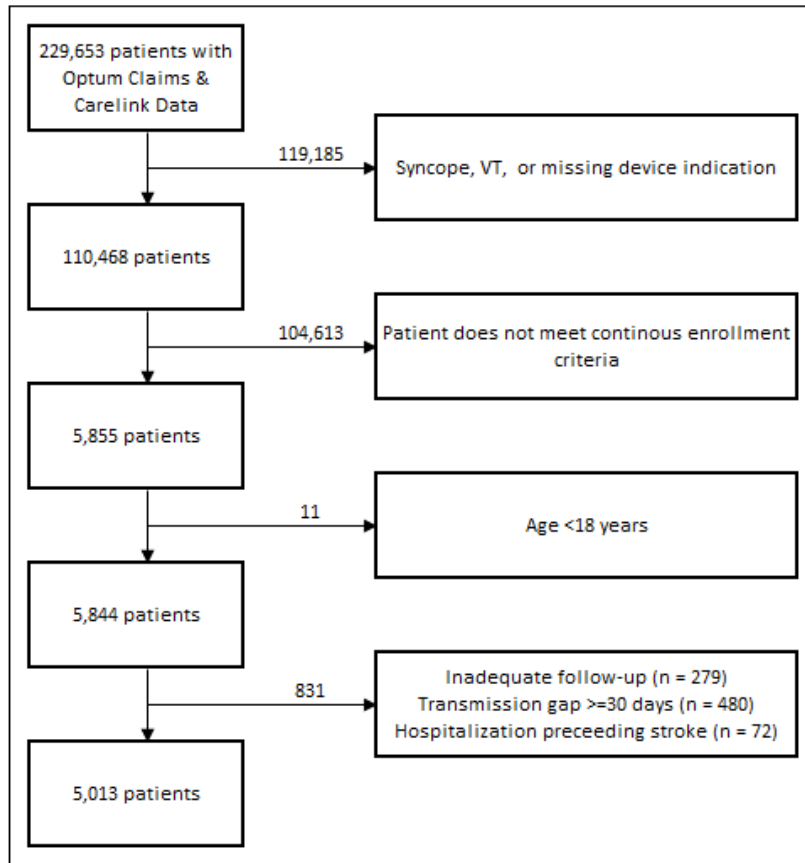


Figure S2: Convergence of mean variable importance.

This convergence plot illustrates the mean importance of each variable in the analysis across bootstrap iterations. For ease of presentation, device parameters show *aggregate* or average variable importance across all their respective features. A point on the plot indicates when a feature was selected by the classification algorithm as a predictor; frequently selected features will have a greater density of points. The convergence of points to a flat line indicates how many bootstraps are needed to reliably estimate variable importance for a given feature. All features except ablation, sleep apnea, and valvular heart disease reached convergence within 1,000 iterations. Given the low variable importance and selection frequency of these three variables, 1,000 bootstraps were considered sufficient for the remainder of the analysis. AFB indicates AF burden; DA, daily activity; DHR, daytime heart rate; NHR, nighttime heart rate; HRV, heart rate variability; OAC, oral anti-coagulation.

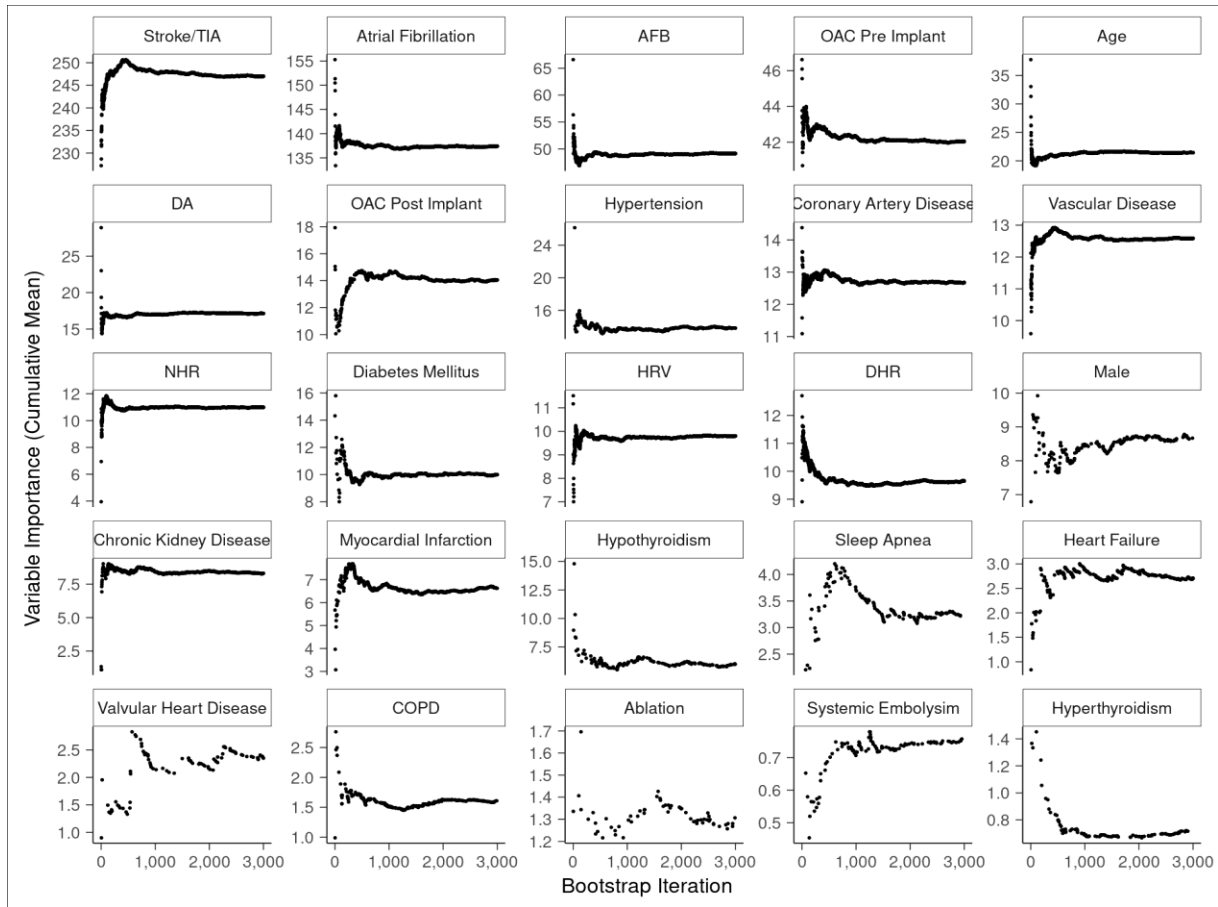


Figure S3: Mean variable importance for patients indicated for AF management. This figure provides a bar plot of mean variable importance, scaled as a percent of total variable importance, by all features in the analysis. For ease of presentation, device parameters show aggregate variable importance across all their respective features. The inset presents the top 30 individual features after stroke/TIA that were selected as predictors at least 5% of the time. AFB indicates AF burden; DA, daily activity; DHR, daytime heart rate; NHR, nighttime heart rate; HRV, heart rate variability; CMA, cumulative moving average; OAC, oral anti-coagulation. All temporal trends are defined as the p -day SMA offset by its CMA.

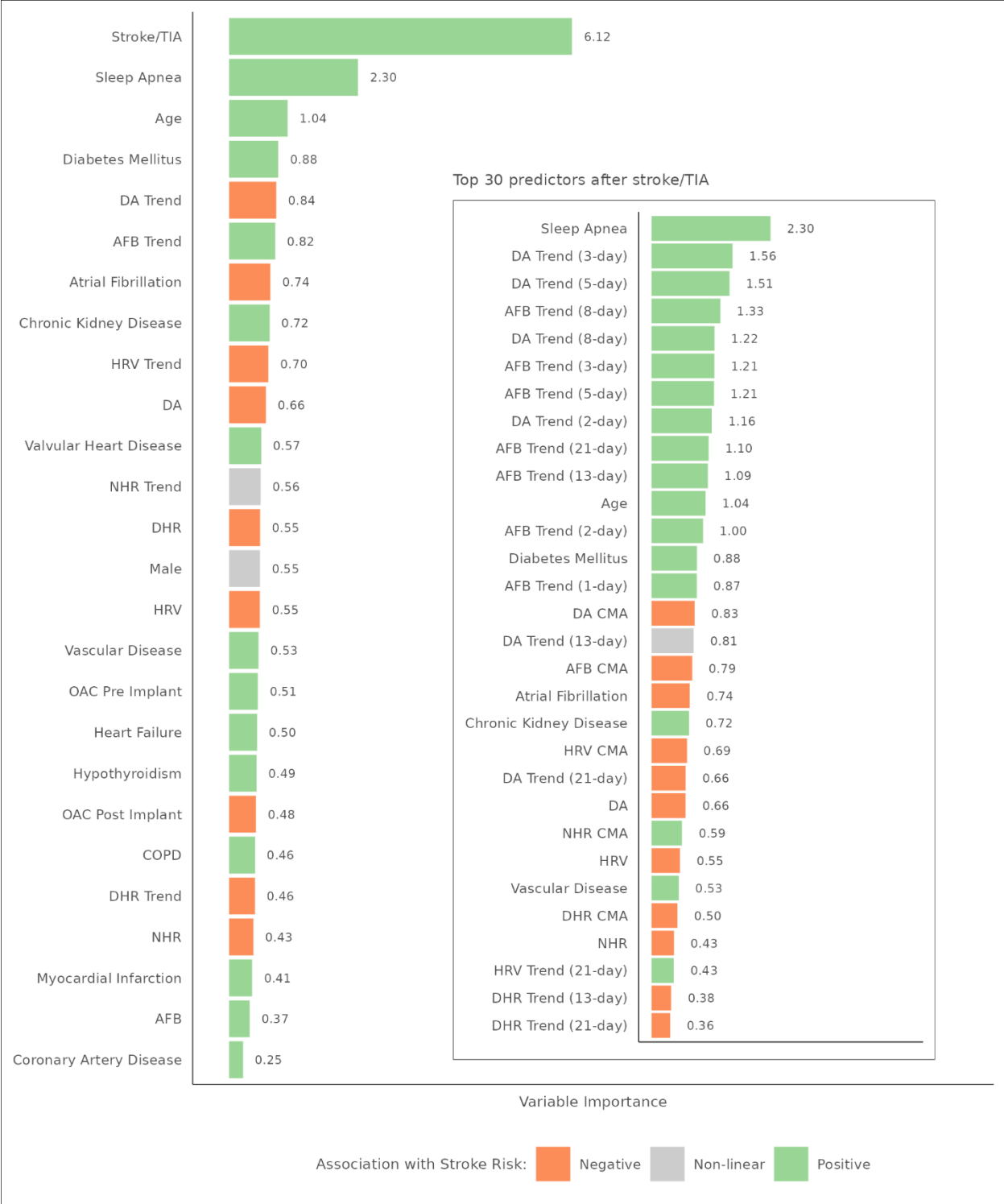


Figure S4: Mean variable importance by CHA₂DS₂-VASc score and feature. This figure provides a bar plot of mean variable importance, scaled as a percent of total variable importance, by CHA₂DS₂-VASc score and all remaining features in the analysis. For ease of presentation, device parameters show aggregate variable importance across all their respective features. The inset presents the top 30 individual features after CHA₂DS₂-VASc score that were selected as predictors at least 5% of the time. AFB indicates AF burden; DA, daily activity; DHR, daytime heart rate; NHR, nighttime heart rate; HRV, heart rate variability; CMA, cumulative moving average; OAC, oral anti-coagulation. All temporal trends are defined as the *p*-day SMA offset by its CMA.

