Comparison of Sampling Strategies to Address Severe Data Imbalance and Computational Benchmarking for Time-to-Event Predictive Model Development Across Local and High-Performance Computing Environments: Prediction of Alcohol Use Disorder and Opioid Use Disorder Among Arkansas Medical Marijuana Cardholders

MSR157

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BACKGROUND

- Severe class imbalance is a common challenge in clinical predictive modeling given the rarity of many health outcomes[1, 2]:
  - Data sampling & hyperparameter tuning can improve discrimination, but introduce tradeoffs between predictive performance, information retention, & computational burden.[1, 2]
- Computational demands are further amplified by modern time-to-event modeling frameworks that leverage longitudinal data to support dynamic risk prediction[4]:
  - High-performance computing (HPC) environment[1] and parallelization tools (e.g. Apache Spark)[2] offer potential solutions, but comparative evidence across computing environments remains limited.

Objective: Using real-world prediction of opioid use disorder (OUD) and alcohol use disorder (AUD) among medical cannabis (MC) cardholders, landmark supermodels were developed to compare:

1. Random undersampling (RUS) and random oversampling (ROS) across class ratios to identify the performance-optimized sampling strategy under systematic hyperparameter tuning
2. Compare model training runtimes across three computing environments: (a) **standard local server, (b) Apache Spark-enabled local server, (c) HPC environment**

METHODS

Data Source & Study Sample

- Time-to-event datasets were constructed using statewide health insurance claims data between November 2018 – December 2023 from the **Arkansas All-Payer Claims Database (AR-APCD).**[5]
- **Subjects:** Insured (medical + pharmacy benefits), adult (≥ 18 years old) Arkansas MC Cardholders without a recent history of the substance use disorder (SUD) of interest in the past 6 months.
- **Index Date:** May 11th, 2019 (opening date of 1st Arkansas MC dispensary) or receipt date of MC eligibility card, whichever came last
- **Follow-up**: Index date until 1st occurrence of one of the following: 1) New OUD|AUD diagnosis, 2) study end date (Dec. 31st , 2023), 3) health plan disenrollment, 4) death from any cause

Engineered Features [OUD (n=170) | AUD (n=169)]

- Included **demographics**, **acute + chronic comorbidities**, **prescription characteristics**, and **healthcare utilization.**

Model Training/Testing

- **Train/test split:** Randomized 70:30 split at person level
- **RUS & ROS class ratios: (OUD:** 1:1, 1:3, 1:10, 1:25, 1:50, 1:100, full-data | **AUD:** 1:1, 1:3, 1:10, 1:25, full-data**)**
- **Hyperparameter tuning:** 90 iterations with 5-fold cross validation
- **Classifiers:** Random Survival Forest (RSF), Support Vector Machine Survival (SVMS), Cox Proportional Hazards (CPH), Random Forest (RF), Logistic Regression (LR)

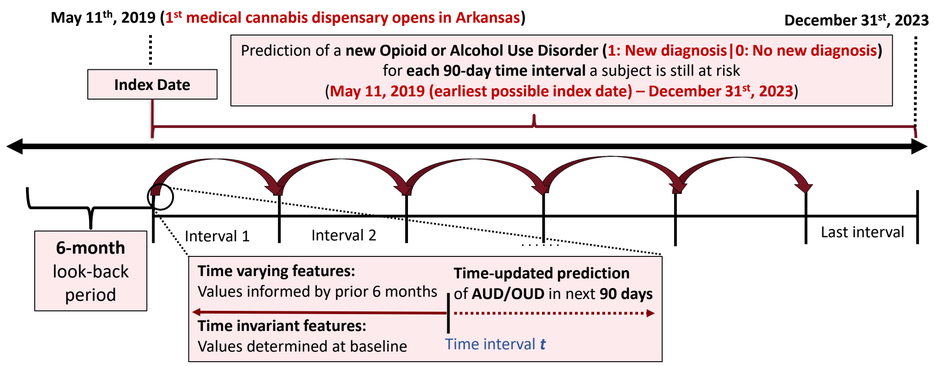
Predictive Performance Evaluation

- **Model discrimination:** cumulative sensitivity/dynamic specificity AUC (**C/D AUC**)
- **Model calibration:** horizon-aligned Inverse probability of censor weighting (**IPCW**) Brier scores

Computational Benchmarking

- **Absolute training times (minutes)** and **relative speedup** were assessed across three computing environments.
  - Local server environments (w/ & w/o Apache Spark v3.5.4) containerized & ran within HPC environment (96 CPU cores, 768 GB RAM), w/ resources restricted (16 CPU cores/160 GB RAM) to emulate typical clinical analytics setting.
- This work was supported with computing resource allocations (MED230043) awarded through the Advanced Cyberinfrastructure Coordination Ecosystem: Services & Support (ACCESS) program.[6]

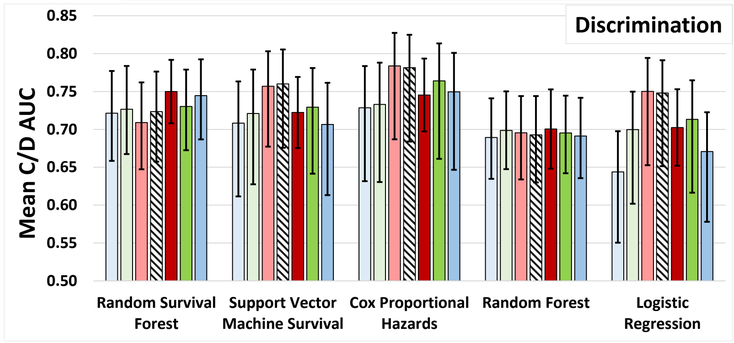
Landmarking Approach

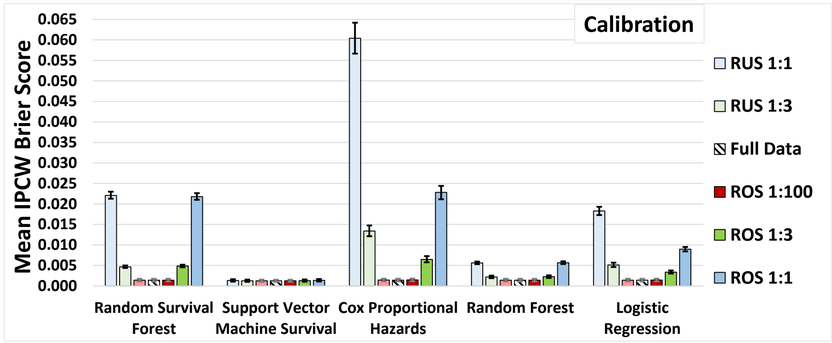


RESULTS

Predictive Performance Across Sampling Strategies: Opioid Use Disorder

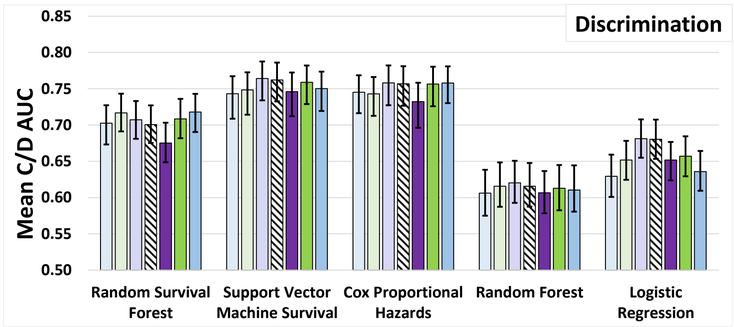
A total of **53,426 Arkansas MC cardholders** met eligibility criteria, of which **364 (0.68%)** received a new **Opioid Use Disorder** diagnosis during the follow-up period.

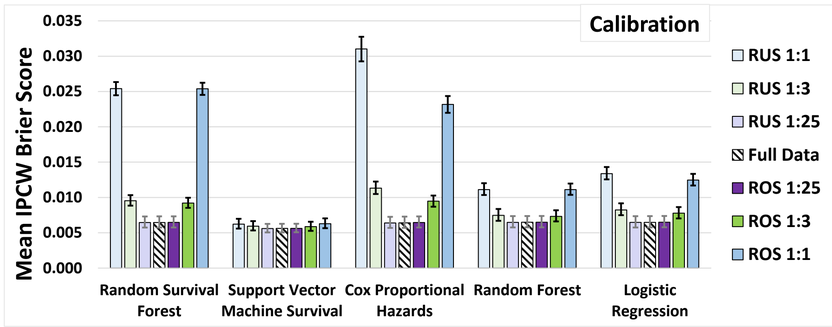




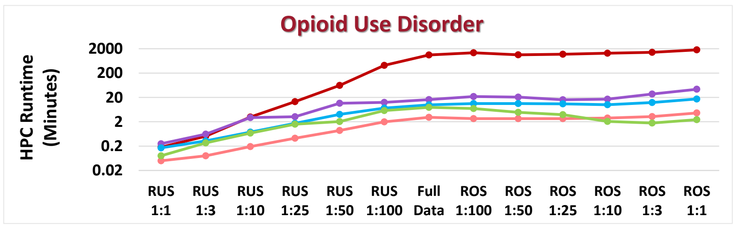
Predictive Performance Across Sampling Strategies: Alcohol Use Disorder

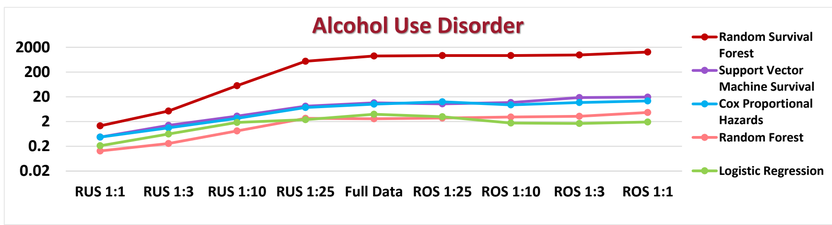
A total of **53,877 Arkansas MC cardholders** met eligibility criteria, of which **1,680 (3.12%)** received a new **Alcohol Use Disorder** diagnosis during the follow-up period.



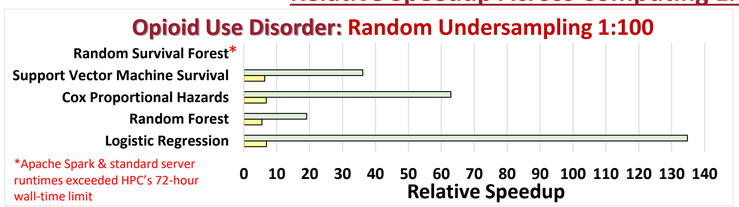


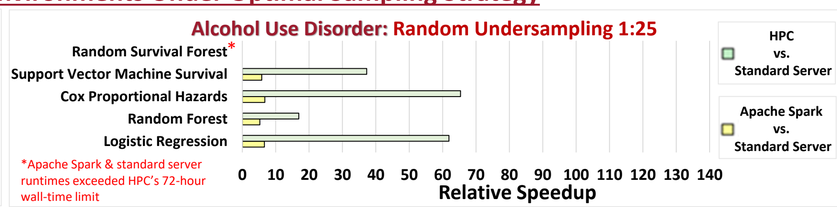
HPC Training Runtimes Across Sampling Strategies





Relative Speedup Across Computing Environments Under Optimal Sampling Strategy





CONCLUSION

- ✓ Sampling strategy had minimal impact on discrimination after hyperparameter tuning.
- ✓ Model choice dominated discriminative performance across all sampling configurations
- ✓ Calibration deteriorated at 1:1–1:3 sampling ratios but stabilized at ≥1:10 imbalance
- ✓ Parallelization substantially improves development speed, particularly when training computationally intensive models
  - ✓ Apache Spark achieved up to ~7× speedup compared to standard computing
  - ✓ High performance computing achieved up to ~190× speedup compared to standard

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