Evaluating Algorithmic Fairness in Predicting Temporal Alcohol Lapse Risks with Machine Learning Models

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Overview and Goals

Alcohol Lapse Prediction

- Developed an XGBoost machine learning model to predict alcohol lapses in the next 24 hours using ecological momentary assessments (EMA; Wyant et al., 2023)
- Model has exceptional performance when predicting lapses for new individuals (mean auROC = .90)
- Locally important features can identify the factors that contribute to lapse risk for any specific person and moment in time
- A "smart" digital therapeutic (smart DTx) could use algorithms based on this model to monitor lapse risk and recommend personalized, optimal interventions and other supports for momentary risks

Algorithmic Bias

- Less privileged, marginalized groups display mental health treatment disparities due to barriers related to affordability, accessibility, availability, and acceptability of mental healthcare
- Smart DTx can partially address these barriers by providing 24/7/365, affordable, personalized support
- However, if embedded algorithms perform relatively worse for less privileged groups, their use may exacerbate rather than reduce treatment disparities

GOAL: Evaluate potential algorithmic bias across historically privileged and unprivileged groups

Methods

Participants

- N = 151
- Early remission from Alcohol Use Disorder
- Endorsed abstinence goal

Procedure

- Personal sensing via smartphone for up to 3 months
- 4x daily (craving, affect, efficacy, risky situations, stressful events, pleasant events)
- Self-reported lapses back to alcohol use

Machine Learning Model

- XGBoost classification model
- Features based on previous EMA
- Provides hour-by-hour probability for future (next 24 hour) lapse

Sensitive Attributes

- **Race/Ethnicity**: Non-hispanic White vs. People of Color
- **Sex**: Male vs. Female
- **income**: above 50% of median personal income in Madison ($15k) vs. below
- **age**: 55 or younger vs. above 55

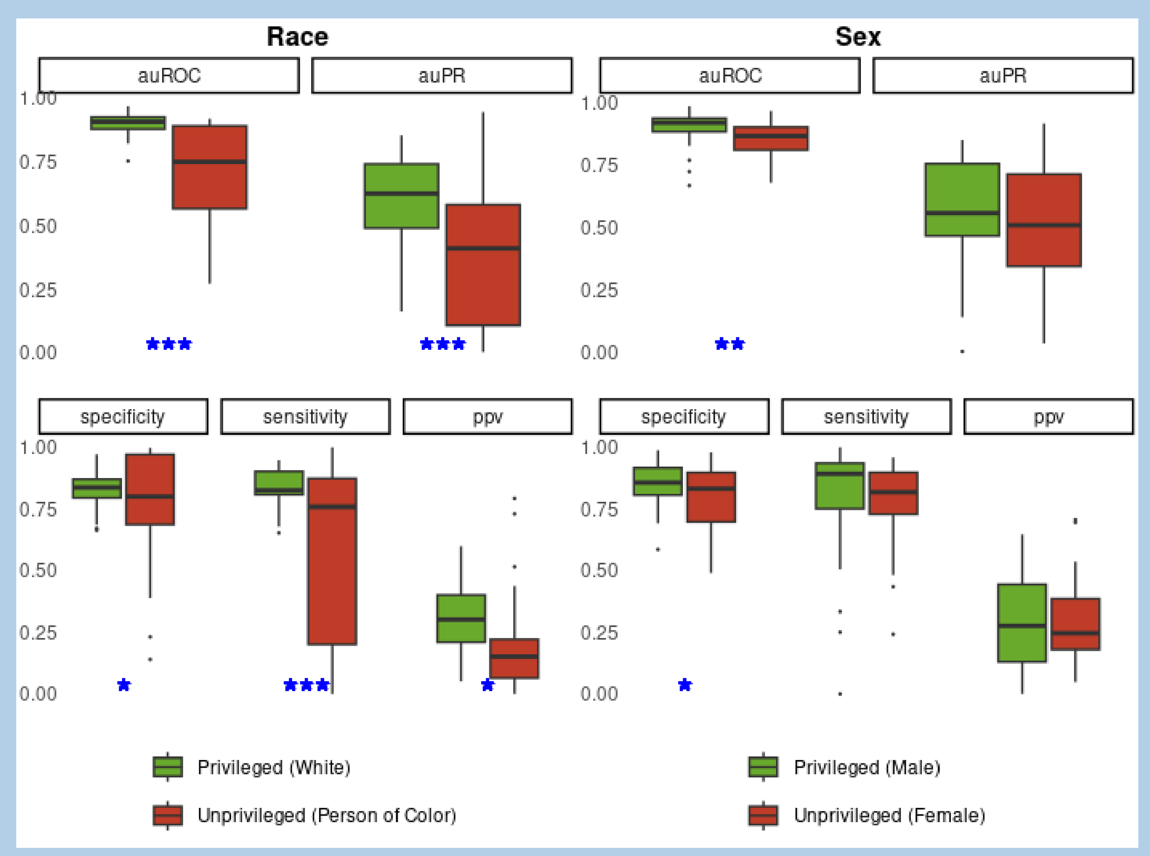
Performance Metrics

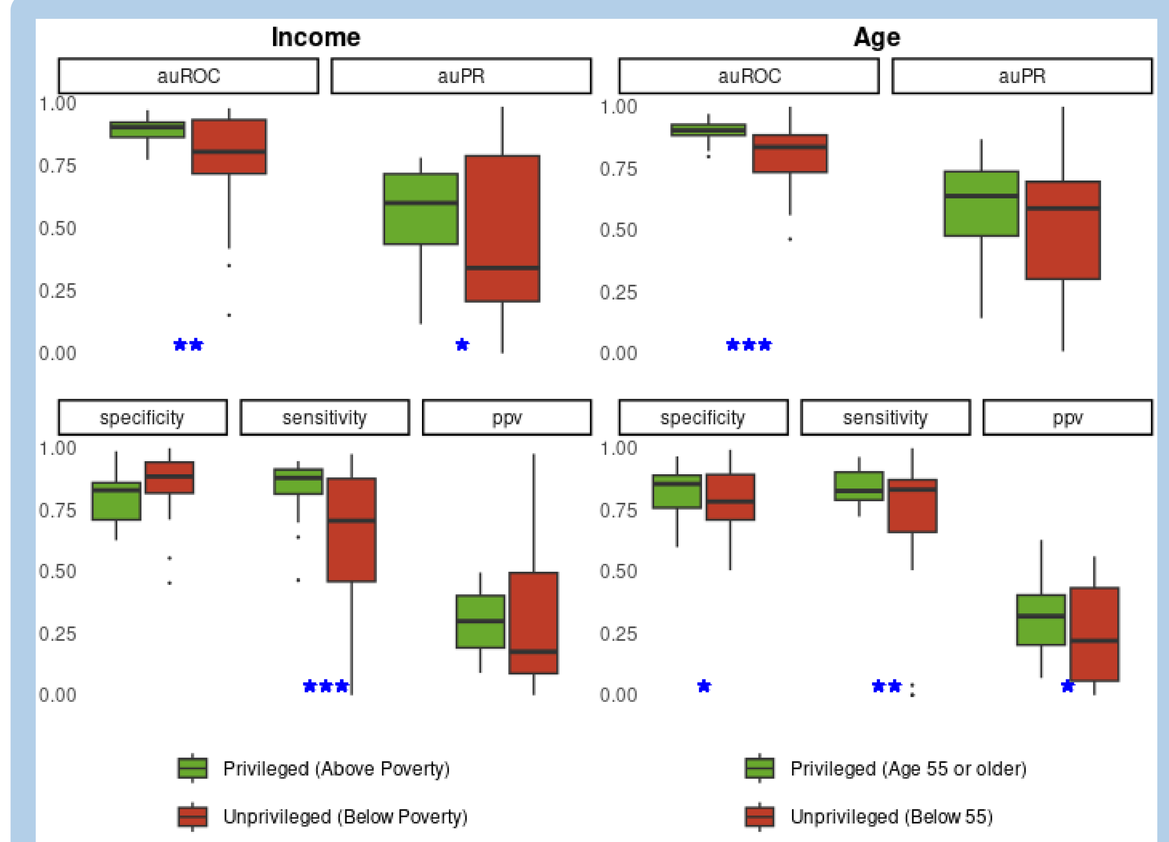
- auROC: true positive rate (sensitivity) against true negative rate (specificity) across thresholds
- auPR: sensitivity against positive predictive value (ppv) across thresholds

Statistical Analysis

- 30 held-out performance estimates (from nested k-fold cross validation) for each metric
- Posterior probabilities of group differences estimated using Bayesian generalized mixed effect models

Results





- Models perform systematically better for White individuals than People of Color.
- auROCs are higher for males than females, probably primarily driven by specificity.
- Both auROCs and auPRs are higher in people with higher income, probably due to sensitivity.
- auROCs, sensitivity, specificity and ppv are significantly higher for younger population.

Conclusions

- Substantially poorer model performance for people of color
- Modestly poorer model performance for groups defined by sex, income, and age
- Representation in training data is clearly important
- Bias may also result from selection of features using domain expertise based on decades of research focused on predominately white men

Next Steps

- Evaluate methods to reduce algorithmic bias
  - More representative training data (NIDA project)
  - Resampling to increase representation
  - Modified cost functions to differential penalize errors based on privilege
  - Control for privilege when predicting
  - More representative features
- Expand evaluation of privilege
  - Rural group, Education
  - AUD Severity
  - Intersectional analyses
  - Bias in treatment/support recommendations