Assessing Demographic Variability in Machine Learning Model Performance to Predict Alcohol Lapses

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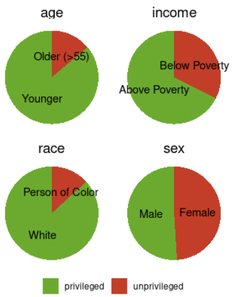

Overview and Goals

Alcohol Lapse Prediction

- Developed an XGBoost machine learning model to predict alcohol lapses in the next 24 hours using ecological momentary assessments (EMA) (INSERT REF)
- Model has exceptional performance when predicting lapses for new (held-out) individuals
- 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

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

Performance Metrics

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-   auROC, auPRC, PPV, sensitivity, specificity
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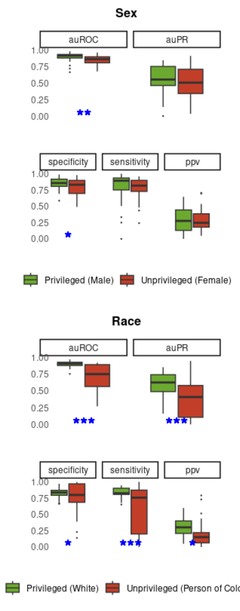
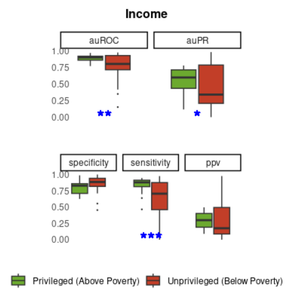
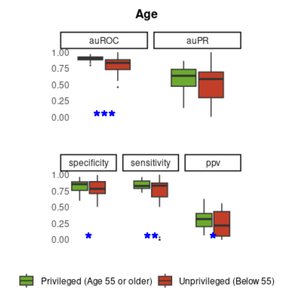
Statistical Analysis

- 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







- auROCs are higher for males than females, probably primarily driven by specificity.
- Models perform systematically better for White individuals than People of Color.
- Both auROCs and auPRs are higher in people with higher income, probably due to significant differences in sensitivity.
- auROCs, sensitivity, and specificity are significantly higher for younger population. auPRs are not significantly different between the two groups, but ppv is higher in younger people.

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
    - Intersectional analyses
    - Bias in treatment/support recommendations