Dynamic lapse risk prediction in a national sample of individuals with opioid use disorder using personal sensing and machine learning

Kendra Wyant[aff-1] and John J. Curtin[aff-1]

[aff-1]Department of Psychology, University of Wisconsin-Madison

Abstract

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Introduction

Methods

Transparency and Openness

We adhere to research transparency principles that are crucial for robust and replicable science. First, we published this study's protocol as a pre-registered report prior to data collection (Moshontz et al., 2021).

Second, we followed the Transparent Reporting of a multivariable prediction model for Individual Prognosis Or Diagnosis extension for Artificial Intelligence (TRIPOD+AI) guidelines for reporting clinical prediction models (Collins et al., 2024). A TRIPOD+AI checklist is available in this manuscripts supplemental materials.

Finally, our data, questionnaires, and other study materials are publicly available on our OSF page (https://osf.io/zvm7s/overview) and our annotated analysis scripts and results are publicly available on our study website (https://jjcurtin.github.io/study_risk2/).

Participants

Procedure

All procedures were approved by the University of Wisconsin-Madison Institutional Review Board (Study #2019-0656). All participants provided written informed consent.

Measures

Individual Differences

Ecological Momentary Assessment

Geolocation Sensing

Data Analytic Strategy

Data preprocessing, modeling, and Bayesian analyses were done in R using the tidymodels

ecosystem (Goodrich et al., 2023; Kuhn, 2022; Kuhn & Wickham, 2020). Models were trained

and evaluated using high-throughput computing resources provided by the University of

Wisconsin Center for High Throughput Computing (Center for High Throughput Computing,

2006).

Feature Engineering

Features were engineered from two types of data:

1. Static individual differences in demographic and OUD characteristics.
2. Dynamic EMA and geolocation sensing data.
- geolocation - within 50 meters of a known location

We imputed missing data using median imputation for numeric features and mode imputation for

nominal features. We selected coarse median/mode methods for handling missing data due to the

computational costs associated with more advanced forms of imputation (e.g., KNN imputation,

multiple imputation). Importantly, our imputation calculations are done using only held-in data

and can be applied to any new observation.

Prediction Windows and Labels

- Window starts 6am in participants own timezone (derived from gps)

Model Selection

Our performance metric for model selection and evaluation was area under the Receiver

Operating Characteristic curve (auROC). .

The best model configuration was selected using 6 repeats of participant-grouped 5-fold

cross-validation. Folds were stratified by a between-subject measure of our outcome (no lapse

vs. any lapse).

Model configurations differed on:

1. Statistical algorithm (and hyperparameter tuning)
2. Resampling of minority outcome. All resampling was exclusively done with only held-in

   training data to prevent biasing performance estimates (Vandewiele et al., 2021).

We repeated the above process to select a best baseline model that was limited to features derived

from individual differences in demographics and OUD characteristics.

Model Evaluation

We used a Bayesian hierarchical generalized linear model to estimate the posterior distribution

and 95% credible intervals (CI) for auROC for the 30 held-out test sets for our best performing

model. We used weakly informative, data-dependent priors to regularize and reduce overfitting.

Random intercepts were included for repeat and fold (nested within repeat).

• Model contrast

Using the same 30 held-out test sets, we calculated the median posterior probability and 95%

Bayesian CI for auROC for each model separately by gender (not male vs. male), race/ethnicity

(Hispanic and/or non-White vs. non-Hispanic White), income (below poverty line vs. above

poverty line), geographic location (small town/rural vs. urban/suburban), and education (high school or less vs. some college). We conducted Bayesian group comparisons to assess the likelihood that each model performs differently by group.

Calibration

We calibrated our probabilities using Platt scaling. We calculated Brier scores to assess the accuracy of our raw and calibrated probabilities for our best model. Brier scores range from 0 (perfect accuracy) to 1 (perfect inaccuracy). We provide calibration plots for the raw and calibrated probabilities in the manuscript and histograms of predicted probabilities by true lapse outcome in the supplement.

Feature Importance

Results

Participants

We recruited 451 participants across 47 states in the United States from April 2021 through December 2024. A total of 336 participants were eligible, consented, and remained on study for at least one month. Eleven participants were excluded due to unusually low adherence[1], 13 participants were excluded due to insufficient context data for geolocation points[2], 1 participant was excluded due to geolocation data indicating they were not residing in the United States, 10 participants were excluded due to evidence of careless responding on EMAs. Our final analysis

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[1]One participant completed only 3 EMA prompts over 88 days and 10 participants had fewer than 20 geolocation points per day on average.

[2]We required participants have at least two contextualized locations other than their home.

sample consisted of 300 participants. Participant demographic and OUD characteristics is

presented in Table 1.

Table 1: Demographic and Clinical Characteristics

	N	%
Age		
18-21	2	0.7
22-25	7	2.3
26-35	108	36.0
36-45	106	35.3
46-55	60	20.0
56-65	13	4.3
Over 65	4	1.3
Gender		
Man	158	52.7
Woman	135	45.0
Non-binary	4	1.3
Not listed above	2	0.7
Orientation		
Straight, that is, not gay or lesbian	238	79.3
Lesbian or gay	16	5.3
Bisexual	39	13.0
Not sure	1	0.3
Not listed above	4	1.3
Race and Ethnicity (select all that apply)		
American Indian/Alaskan Native	17	5.7
Asian	4	1.3
Black/African American	44	14.7
Native Hawaiian/Other Pacific Islander	3	1.0
White/Caucasian	237	79.0
Hispanic, Latino, or Spanish origin	25	8.3
Not listed above	5	1.7
Geographic Location		
small town/rural	62	20.7
urban/suburban	274	91.3
N = 299		

Adherence, Features, and Labels

Mean days on study across participants was 298 days (range 32-395 days). 83% of participants (250/300) remained on study for at least six months. EMA adherence was high. On average participants completed 73% of the daily EMA prompts (range 24-100%). Participants provided, on average, 313 daily geolocation points (range 20-825).

Our final feature set consisted of 640 features. The proportion of missing values across features was low (mean=.03, range = 0-.12). Across participants we generated a total of 88,973 day-level labels. Forty percent of participants (119/300) reported an opioid lapse while on study (mean=5.73, range 0-117). This resulted in 1.93% of the labels positive for lapse (1,720/88,973 labels).

Performance

The best model configuration used an xgboost statistical algorithm and up-sampled the minority class.[3] The median posterior probability for the best model was 0.93, with narrow 95% CI ([0.92, 0.94]).

We compared our best model's performance to a baseline model that only used information gathered at intake (i.e., individual differences in demographic and OUD characteristics) to evaluate the incremental predictive value of adding dynamic features. The median posterior probability for the baseline model was 0.74 (95% CI [0.71, 0.77]). A Bayesian

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[3]The best model configuration used 1:4 upsampling of the minority class and the following hyperparameter values: learning rate = .1, tree depth = 1, mtry = 50.

model comparison revealed extremely strong evidence that the best model was more predictive than the baseline model (probability = 1.00).

Our fairness subgroup comparisons revealed no evidence that performance meaningfully differed by geographic location (probability = 0.68), weak evidence that performance differed by education (probability = 0.83), and strong evidence that performance differed by gender, income, and race and ethnicity (probabilities > 0.99). Notably, our model performed better for individuals with an annual income below the federal poverty line compared to individuals above the federal poverty line, thus favoring the disadvantaged group. While differences in performance estimates exist across subgroups, they are not likely clinically meaningful as all of our subgroups yielded median auROCs between 0.91 - 0.94 (Figure 1). A table of fairness subgroup comparisons is available in the supplement.
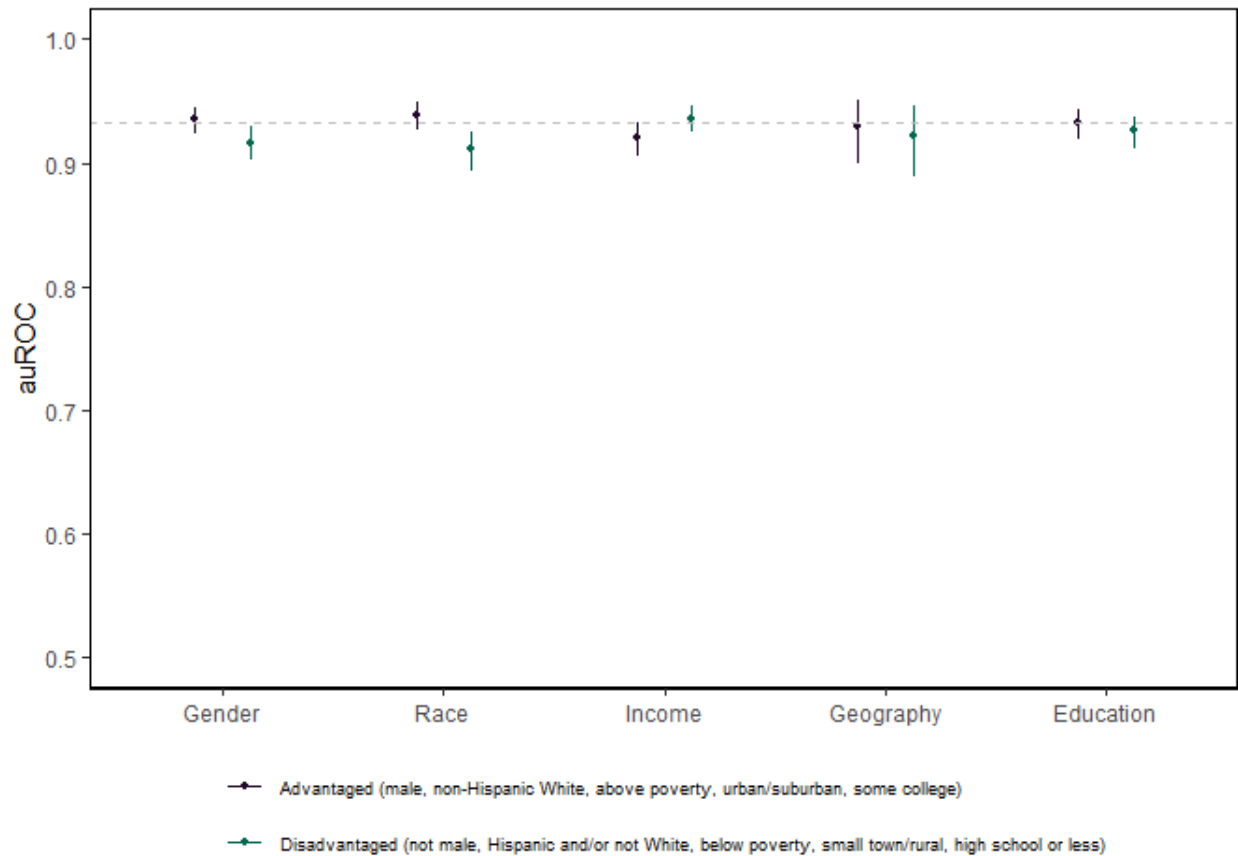
Figure 1: Posterior probabilities for area under the receiver operating curve (auROC) by demographic subgroup. auROC ranges from .5 (chance performance) to 1 (perfect performance). Subgroups advantaged in access to substance use treatment and outcomes (male, non-Hispanic White, above poverty, urban or surburban geographic location, and some college education) are depicted in dark purple. Subgroups disadvantaged in access to substance use treatment and outcomes (not male, Hispanic and/or not White, below poverty, small town or rural geographic location, and high school education or less) are depicted in green. Overall model performance across groups is depicted as the dashed grey line.

Calibration

Our raw model predicted probabilities were generally well-calibrated (brier score = 0.015). We

attempted to improve calibration with Platt scaling but results were comparable (brier score =

0.015). Calibration plots for the raw uncalibrated probabilities and calibrated probabilities with

Platt scaline are presented in Figure 2. Histograms of predicted probabilities by true lapse

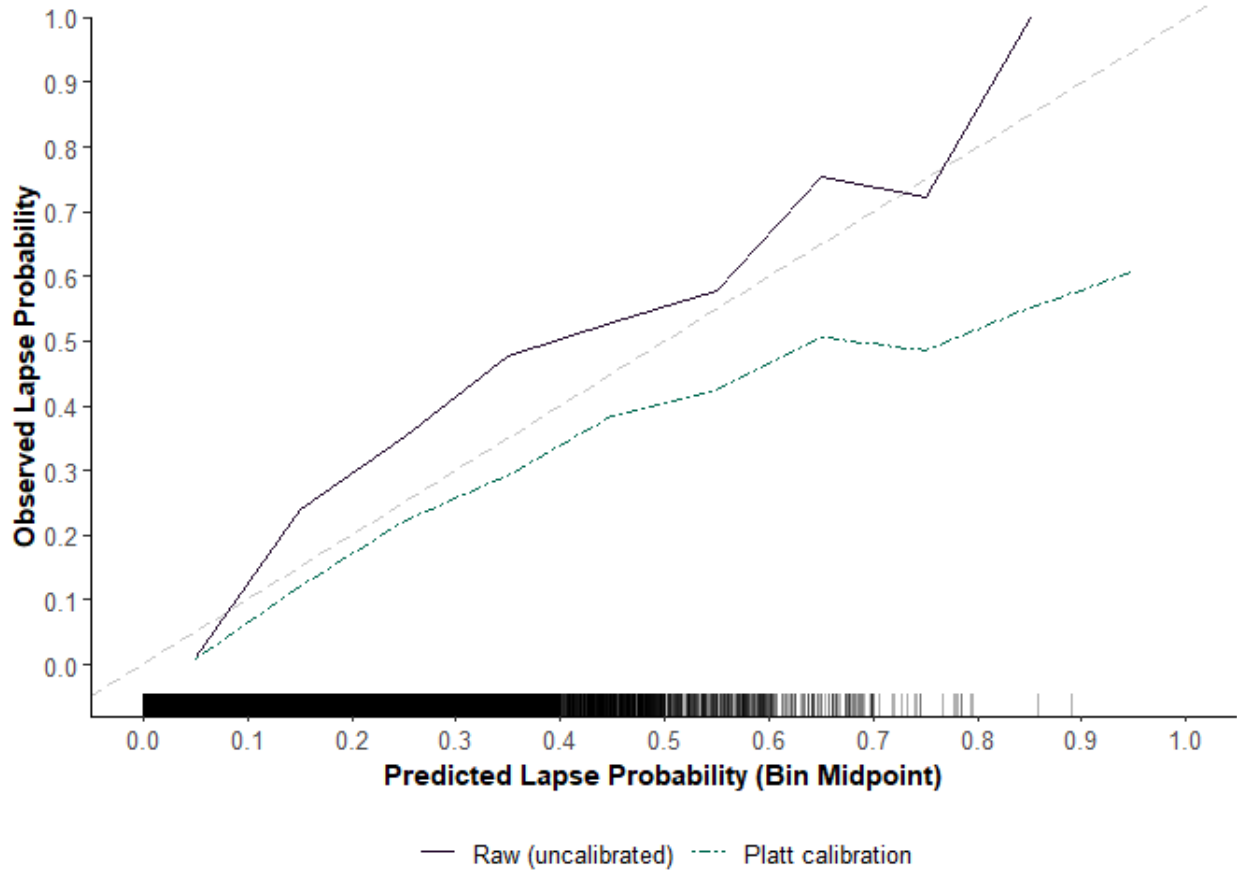outcome are available in the supplement.

Figure 2: Calibration plots of raw and calibrated lapse probabilities. Predicted probabilities (x-axis) are binned into deciles. Observed lapse probability (y-axis) represents the proportion of actual lapses observed in each bin. The dashed diagonal represents perfect calibration. Points below the line indicate overestimation and points above the line indicate underestimation. Raw probabilities are depicted as dark purple lines Platt calibrated probabilities are depicted as green dashed lines.

Feature Importance

For brevity, we are only displaying the top 30 features, as defined by the 30 largest absolute mean shapley values. In the supplement, we provide full figures of all possible feature categories.
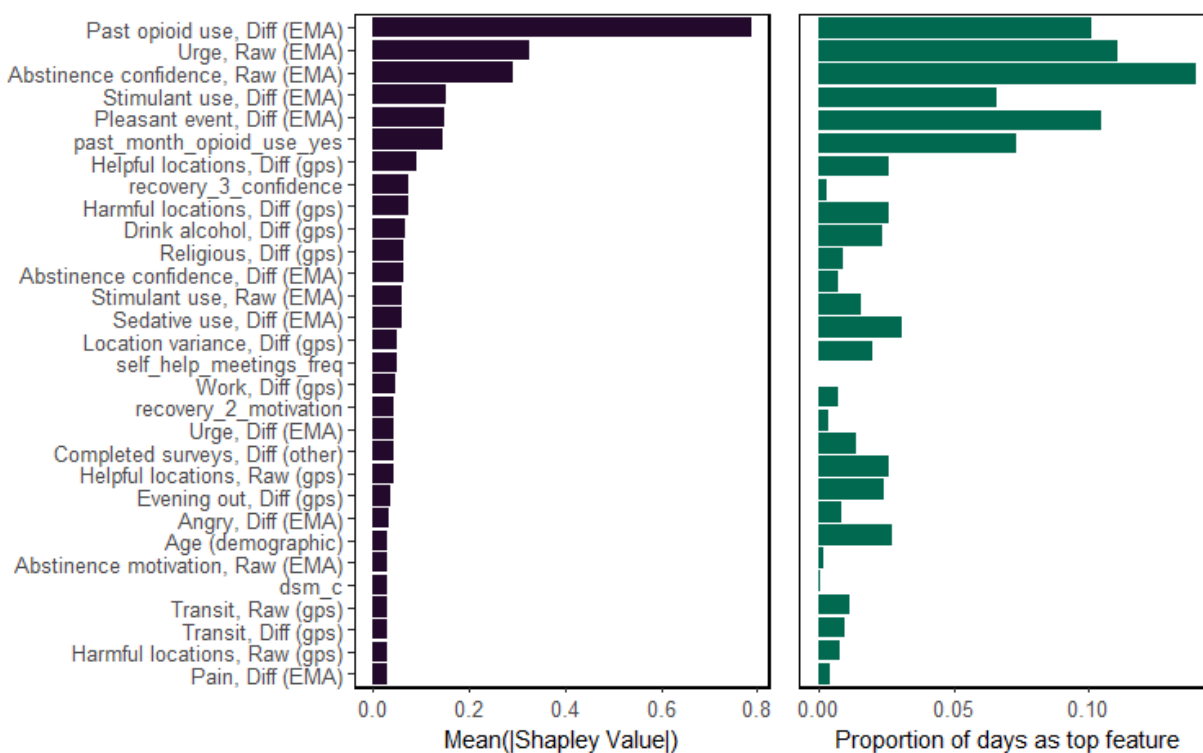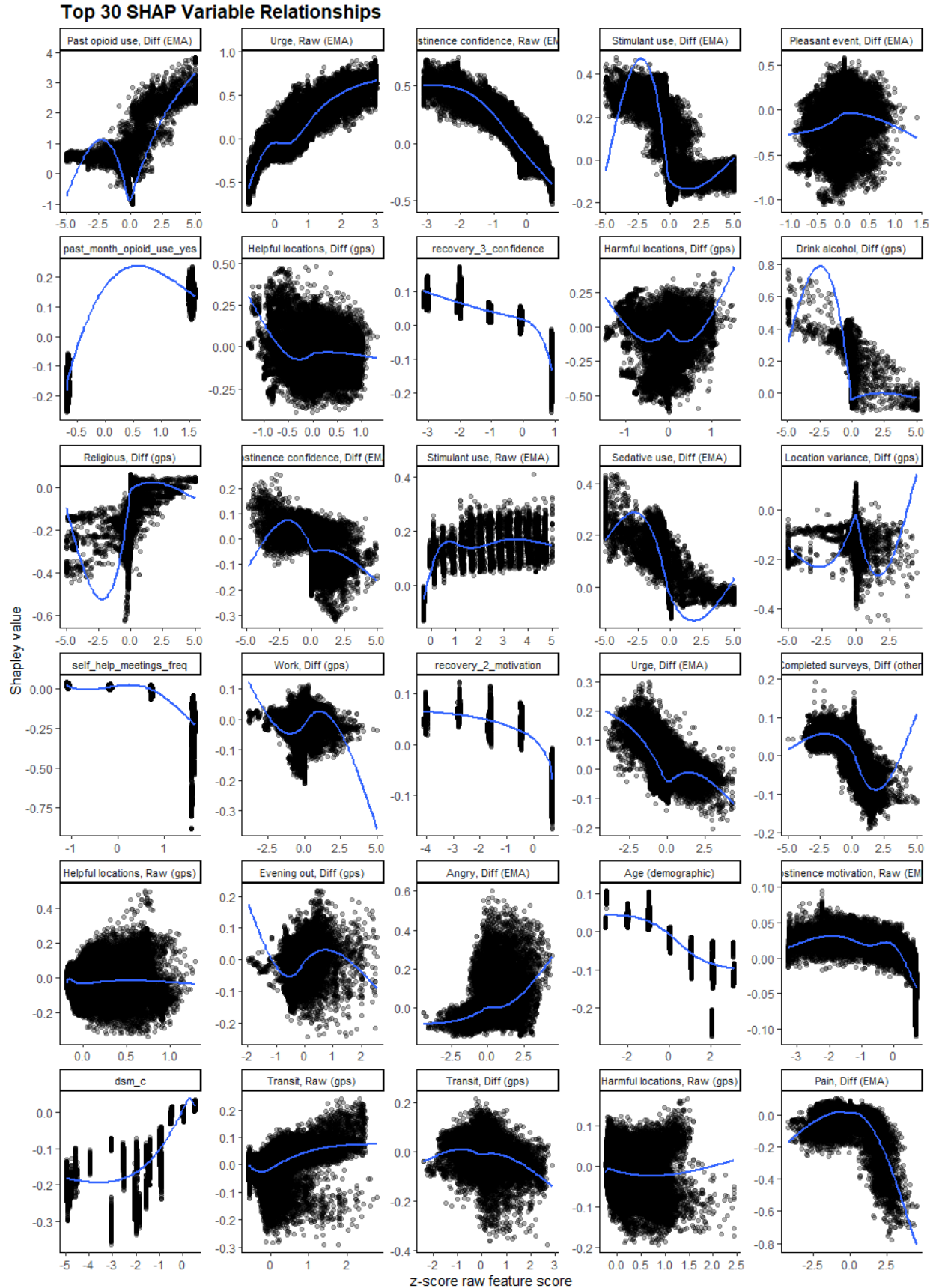
Figure 3

Figure 4: Feature importance partial dependence plots.

Discussion

- Discuss contrast between top global features and "actual" important features (i.e., what comes up day to day as being important). What does this mean for how we traditionally conceptualize feature importance?
- When discussing fairness - we don't look at age. People over 65 is an important group to look at but they were not in our sample
- Decision not include misclassification cost analyses: acknowledge that discrimination and calibration don't equate to clinical utilility. Decision analysis tools, such as net benefit curves could be used to quantify clinical benefit at relevant probability thresholds. Our model is designed to not be used to make decisions about whether or not to treat but to provide model feedback to individuals each day to help them monitor their risk for lapse. Therefore the decision has already been made to always treat. Should these models be used to inform when to deploy more cost-intensive interventions (e.g., communicating risk level to a therapist to initiate contact) these analyses will be important next steps.

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