Using ecological momentary assessment for temporally precise lapse prediction in alcohol use disorder

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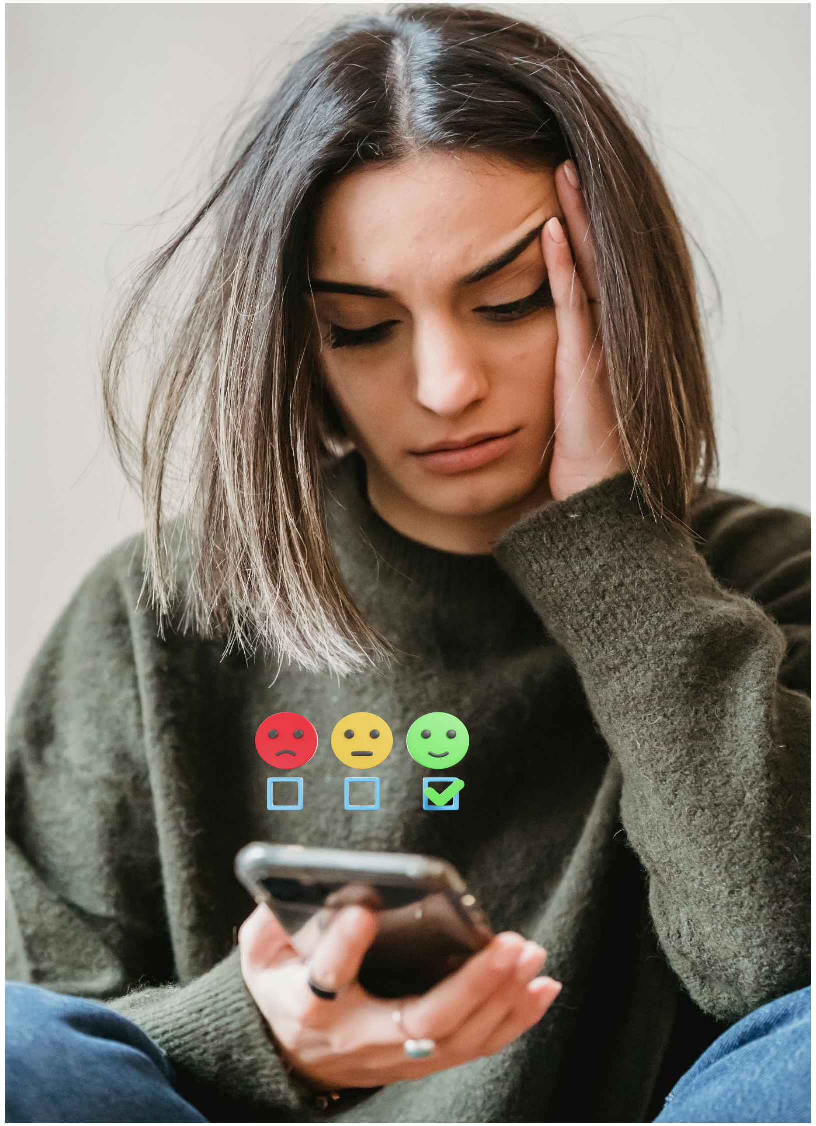


Photo credit: liza summer (pexels.com)

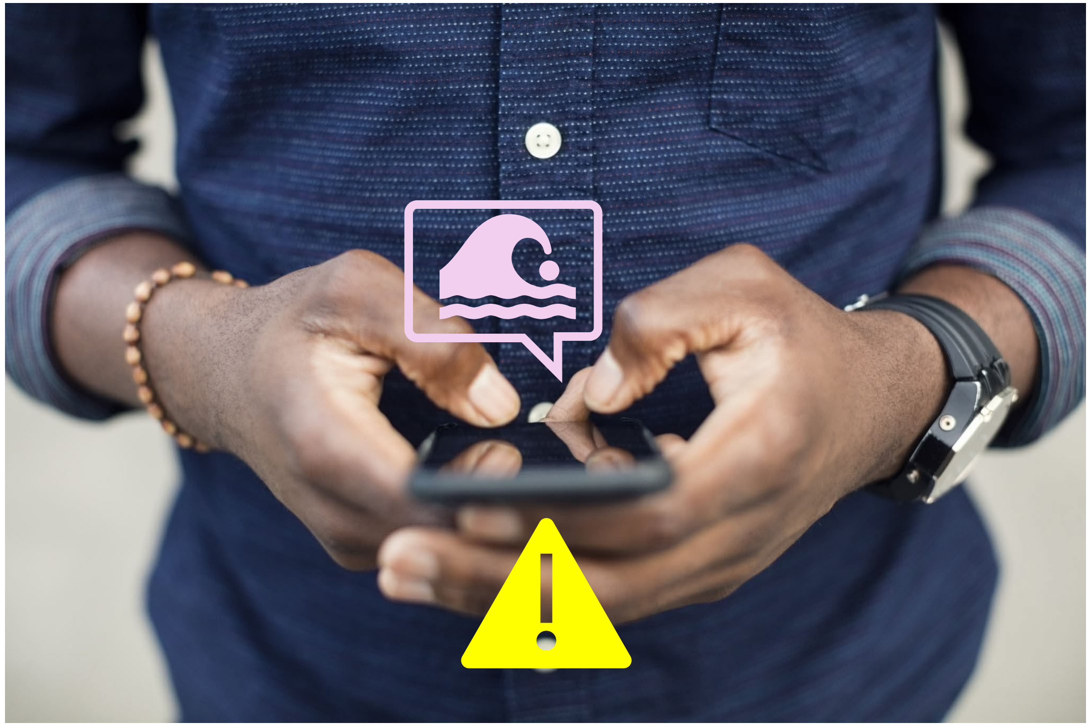
Substance Use Disorders

- In 2022, 46 million U.S. adults with a past year SUD
- Few receive treatment
- Patients often leave treatment without proper supports in place
- *Lapse* = instance of goal-inconsistent substance use

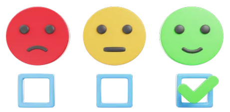
SAMHSA, 2022

Precision Mental Health

- A precision mental health paradigm for adaptive, continuous lapse risk monitoring could be an important step toward preventing relapse and improving continuity of care for SUDs



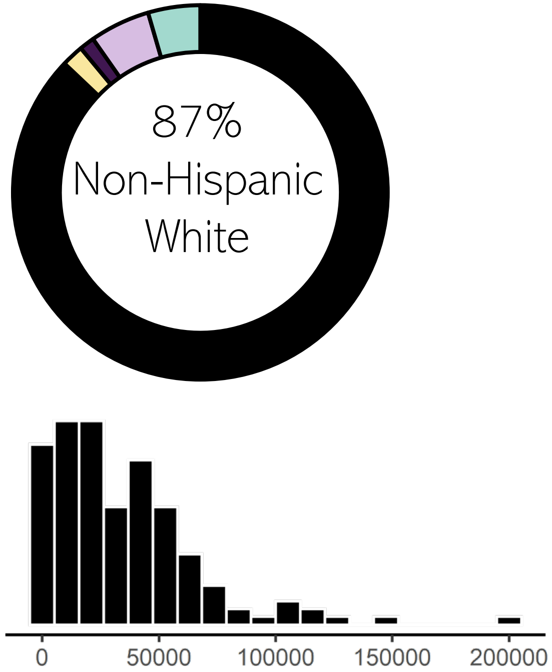
Ecological Momentary Assessment



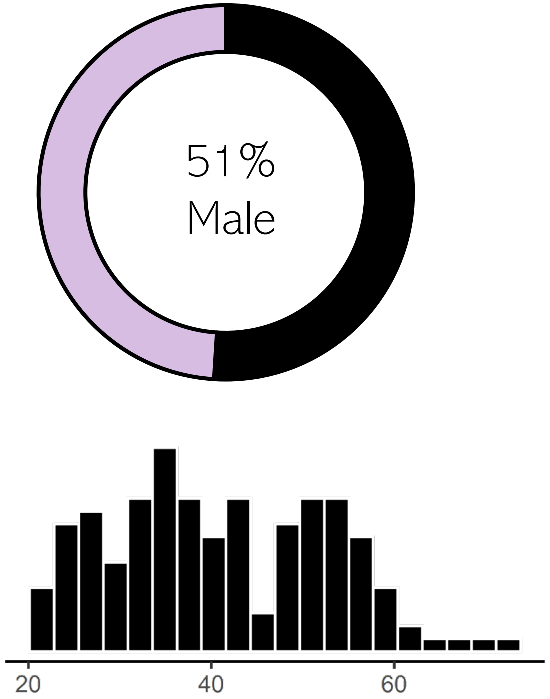
- Direct and frequent insight into subjective feelings and experiences
- Constructs easily map onto well-studied risk factors for lapse
- Appears to be well-tolerated
- **Predicting lapses and interpreting clinically relevant features over a sustained period**

Wyant et al., 2023

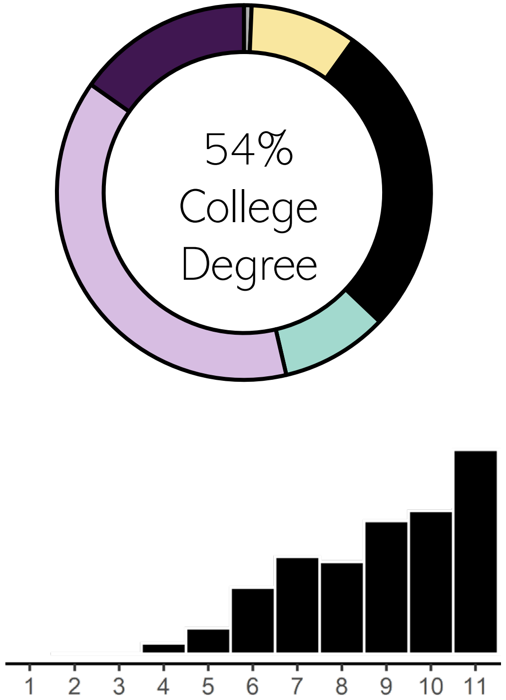
Participants



Income
(M = 34,298)



Age
(M = 41)



AUD Sx
(M = 9)

N = 151; NIAAA (R01 AA024391; John J Curtin)

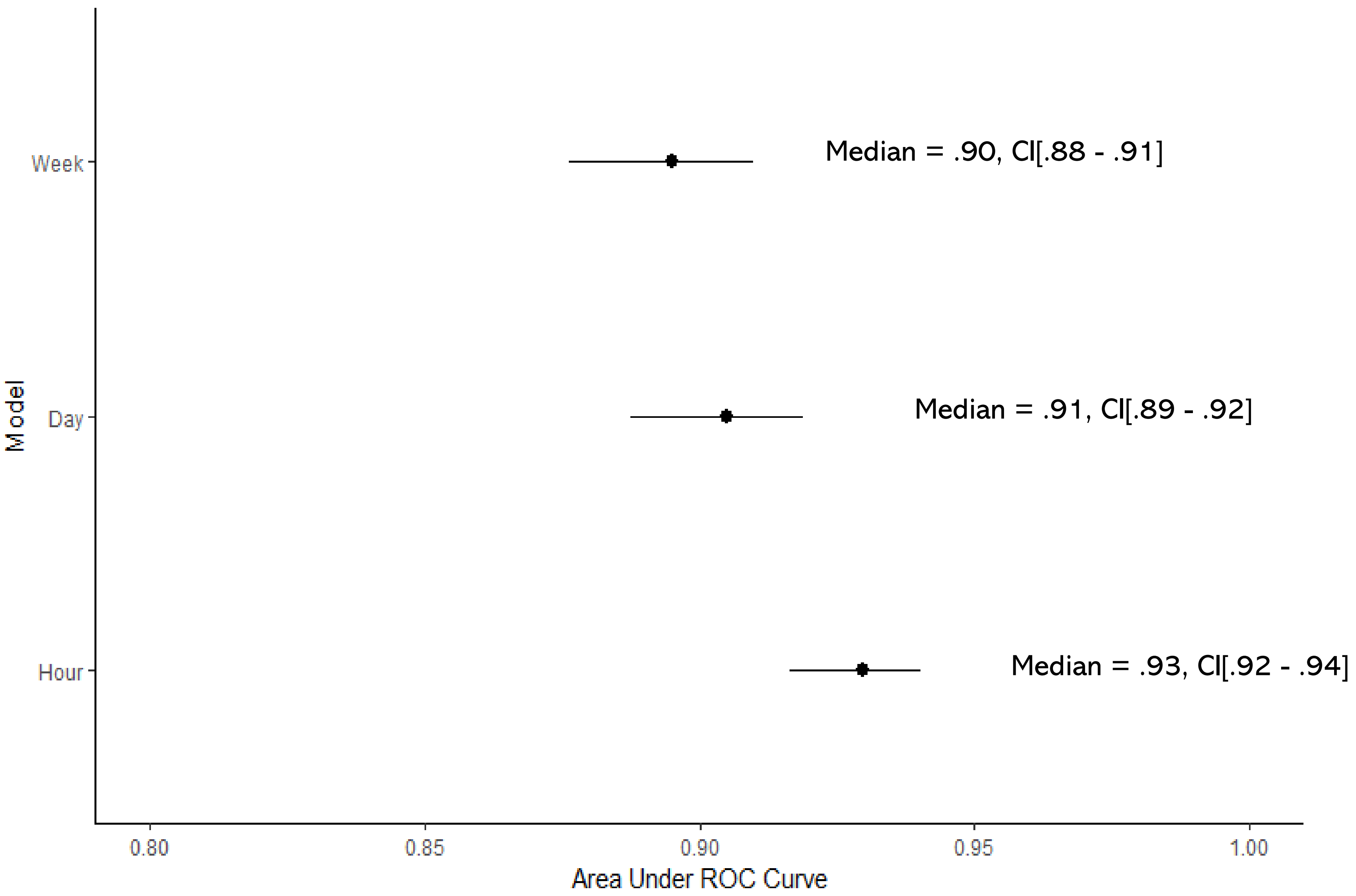
Study Design

- 3-month longitudinal study
- Participants provided 4x daily EMA

Alcohol use	Craving	Stressful events	Future risky situation
	Arousal	Pleasant events	Future stressful event
	Valence	Risky situations	Future efficacy

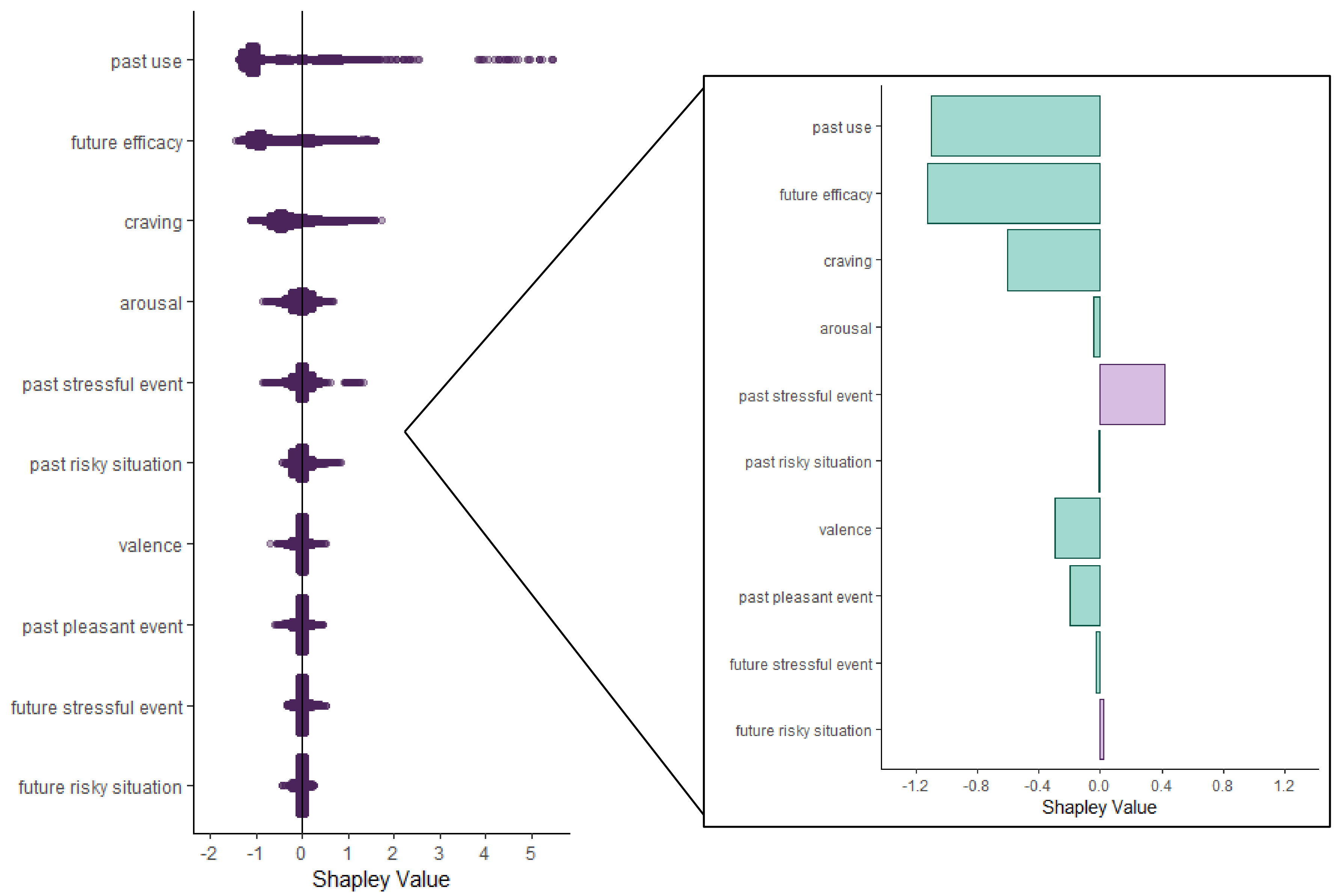
Modeling Decisions

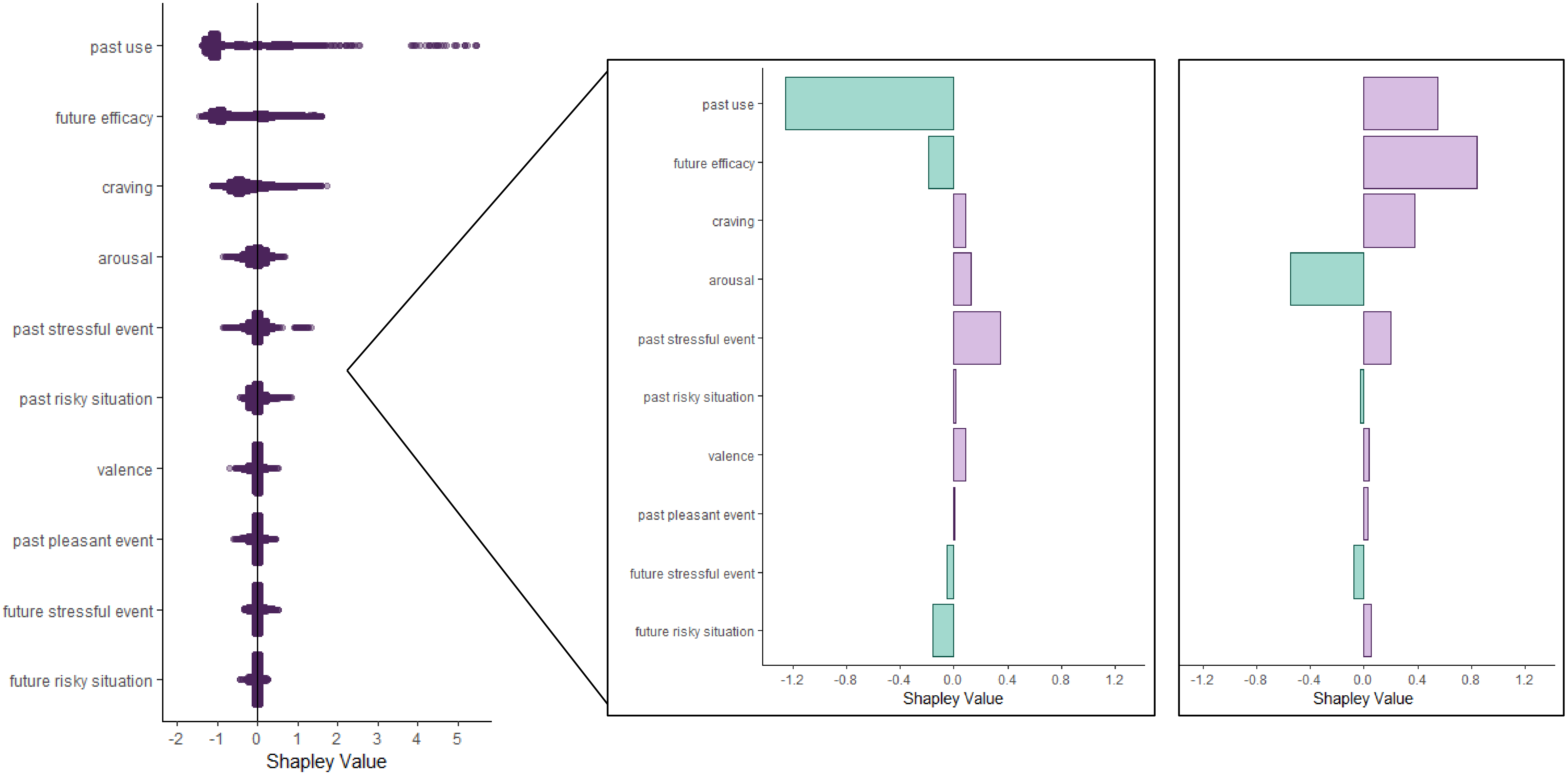
- Next **week**, next **day**, and next **hour** lapse predictions
- Grouped Nested Cross Validation (3 x 10 outer; 1 x 10 inner)
- 286 features engineered from EMA items, day and time of label, missing surveys, and demographics
- True prediction
- Area under the ROC curve (auROC)
- XGBoost



Median = .90, CI[.88 - .91]
Median = .91, CI[.89 - .92]
Median = .93, CI[.92 - .94]
Week
Day
Hour
Model
0.80
0.85
0.90
0.95
1.00
Area Under ROC Curve

past use
future efficacy
craving
arousal
past stressful event
past risky situation
valence
past pleasant event
future stressful event
future risky situation
-2
-1
0
1
2
3
4
5
Shapley Value


past use
future efficacy
craving
arousal
past stressful event
past risky situation
valence
past pleasant event
future stressful event
future risky situation
-2
-1
0
1
2
3
4
5
Shapley Value
past use
future efficacy
craving
arousal
past stressful event
past risky situation
valence
past pleasant event
future stressful event
future risky situation
-1.2
-0.8
-0.4
0.0
0.4
0.8
1.2
Shapley Value



past use
future efficacy
craving
arousal
past stressful event
past risky situation
valence
past pleasant event
future stressful event
future risky situation
-2
-1
0
1
2
3
4
5
Shapley Value
-1.2
-0.8
-0.4
0.0
0.4
0.8
1.2
Shapley Value
-1.2
-0.8
-0.4
0.0
0.4
0.8
1.2
Shapley Value

Photo credit: Kelvin Valerio

- We can predict hour by hour probabilities of lapse at varying levels of temporal precision with excellent performance

- We can characterize the relative importance of features contributing to these risk probabilities for specific individuals at specific moments in time

- These models that predict and characterize immediate risk of lapse are well-suited for *just in time* personalized interventions

Thank you!

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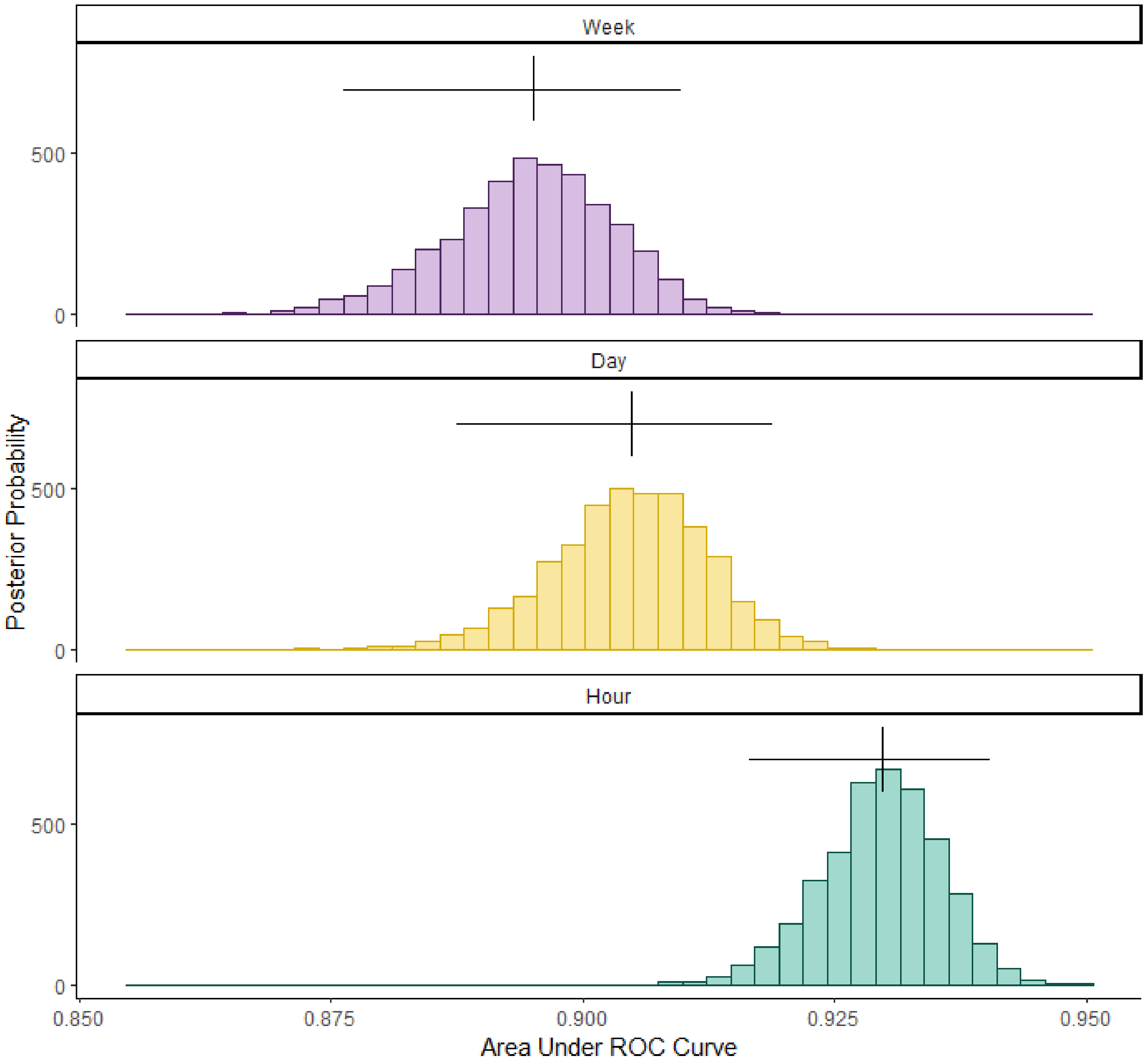
Priors

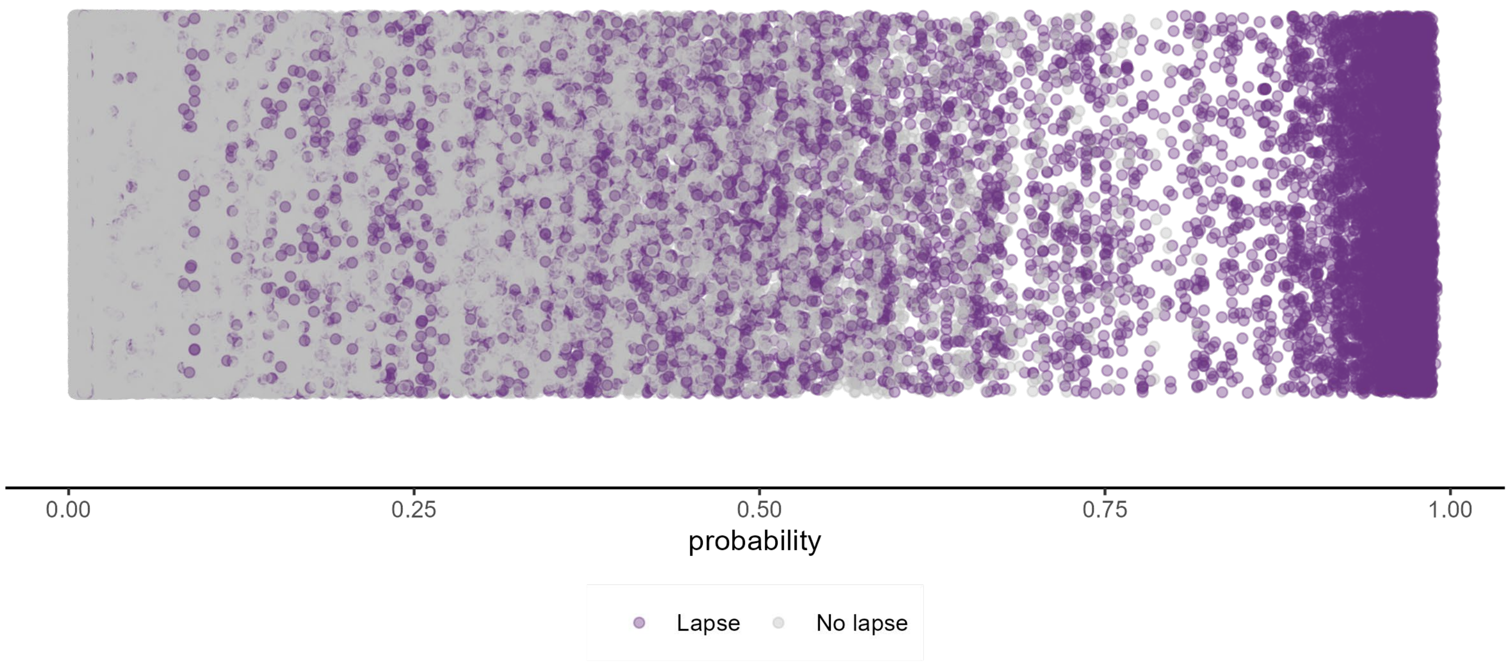
- residual standard deviation ~ normal(location=0, scale=exp(2))
- intercept (after centering predictors) ~ normal(location=2.3, scale=1.3)
- the two coefficients for window width contrasts ~ normal (location=0, scale=2.69)
- covariance ~ decov(regularization=1, concentration=1, shape=1, scale=1).

RStudio Team 2020; Gabry and Goodrich 2023



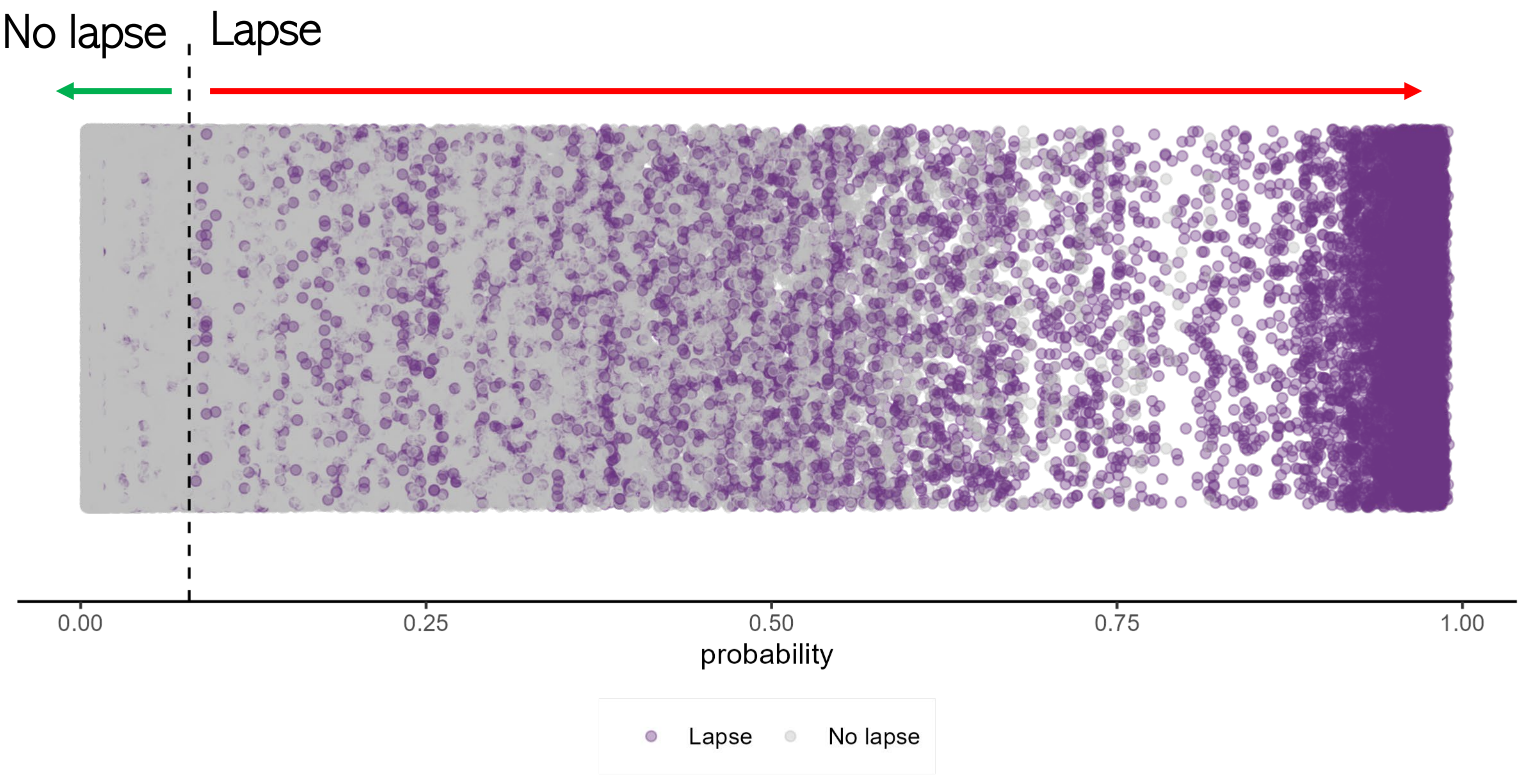
Week
Day
Hour
Posterior Probability
500
0
0.850
0.875
0.900
0.925
0.950
Area Under ROC Curve

Lapse Probabilities



Class Prediction

Dichotomize lapse probability based on a decision threshold



$J = .08$; $N = 274{,}179$

1 day model

Lapse vs No lapse

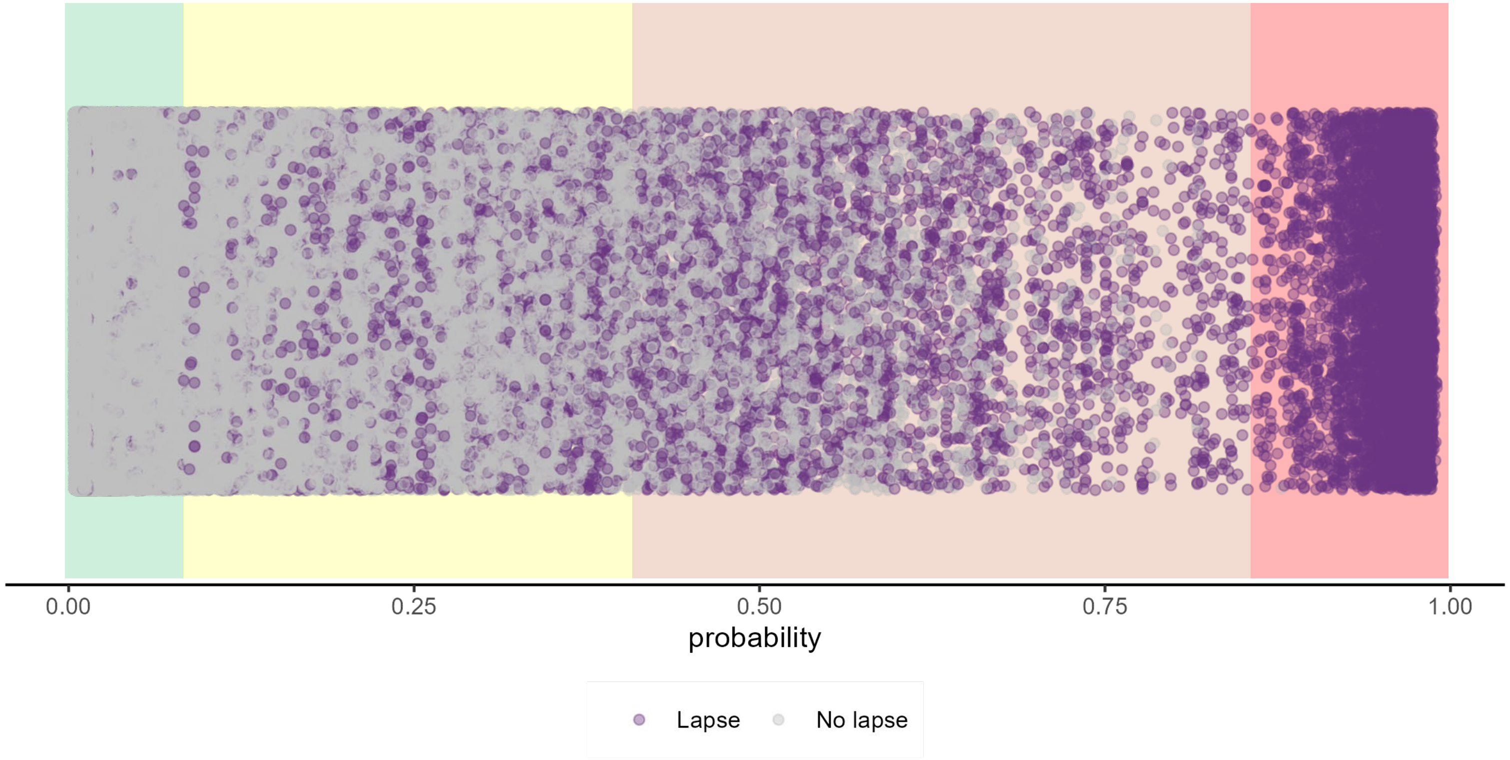
		Truth	
		Lapse	No Lapse
Prediction	Lapse	**TP** 17496	**FA** 40912
	No Lapse	**Misses** 3611	**TN** 212160

Sensitivity	.83
Specificity	.85
Positive Predictive Value	.30
Negative Predictive Value	.99

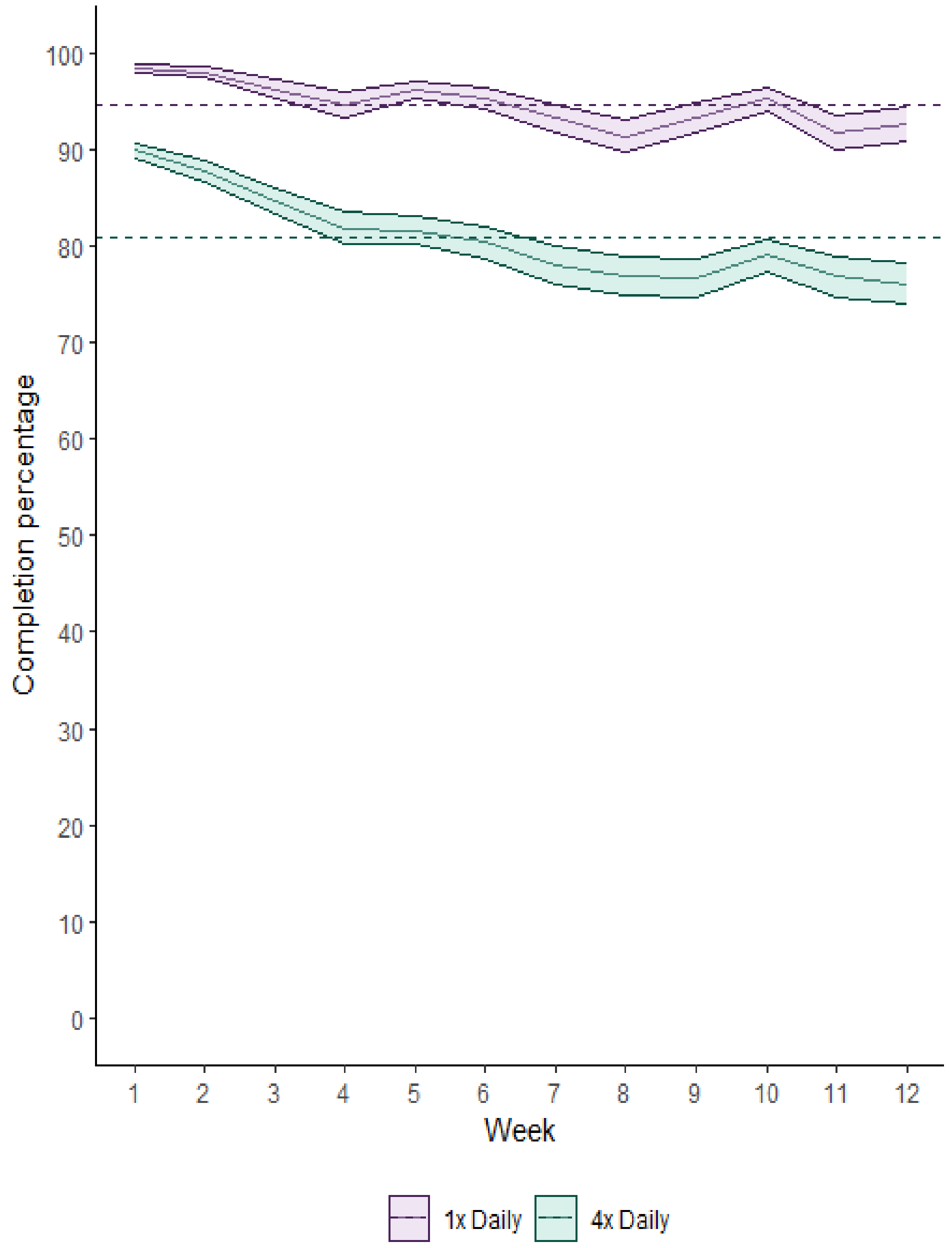
$J = .08$; $N = 274{,}179$

1 day model

Lapse Probabilities



Treatments can be selected based on severity of risk



EMA completion percentage is high

- 81% completion for 4x EMA
- 95% completion for 1x EMA

Wyant et al., 2023