Precision Mental Health for Substance Use Disorders Using Personal Sensing

Kendra Wyant
University of Wisconsin-Madison

April 26, 2024

Capstone Talk

Substance Use Disorders

- In 2022, 46 million U.S. adults with a past year SUD
  - Almost 50% SUDS labeled as moderate to severe
  - Less than 25% received any treatment
- Top reasons for not getting treatment
  - Thought they should be able to handle their substance use on their own
  - Not ready to start treatment
  - Did not know where or how to get treatment
  - Thought it would cost too much
  - Worried about what people would say or think if they got treatment
  - Not having enough time

SAMHSA, 2022

Substance Use Disorders

- In 2022, 46 million U.S. adults with a past year SUD
  - Almost 50% SUDS labeled as moderate to severe
  - Less than 25% received any treatment
- Top reasons for not getting treatment
  - Thought they should be able to handle their substance use on their own
  - Not ready to start treatment
  - Did not know where or how to get treatment
  - Thought it would cost too much
  - Worried about what people would say or think if they got treatment
  - Not having enough time
- Treatment disparities in access to treatment

SAMHSA, 2022

Substance Use Disorders

- In 2022, 46 million U.S. adults with a past year SUD
  - Almost 50% SUDS labeled as moderate to severe
  - **Less than 25% received any treatment**
- Top reasons for not getting treatment
  - Thought they should be able to handle their substance use on their own
  - Not ready to start treatment
  - Did not know where or how to get treatment
  - Thought it would cost too much
  - Worried about what people would say or think if they got treatment
  - Not having enough time
- Treatment disparities in access to mental health treatment

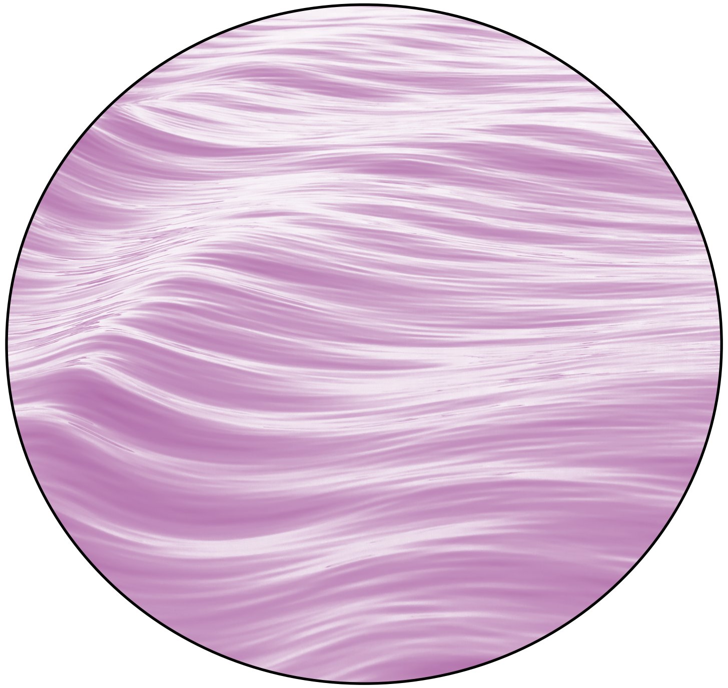
SAMHSA, 2022

Lapse and Relapse

- *Lapse* = instance of goal-inconsistent substance use
- *Relapse* = full return to previous patterns of use
- Lapses are an early warning sign of relapse
- Maladaptive responses to lapses can undermine recovery
- **Lapse prediction may be an important part of treatment and intervention**

Relapse Prevention Literature

- Fluctuating process
- Lapses are preceded by high-risk situations
- High-risk situations differ between individuals and within an individual over time
- Traditional treatment may not be effective for monitoring risk and delivering just-in-time interventions



Digital Therapeutics

- Managing, preventing, or treating a disorder

Digital Therapeutics

- Managing, preventing, or treating a disorder
- Potential to mitigate economic, cultural, and geographic barriers to treatment

Substance Use Disorders

- In 2022, 46 million U.S. adults with a past year SUD
  - Almost 50% SUDS labeled as moderate to severe
  - Less than 25% received any treatment
- Top reasons for not getting treatment
  - **Thought they should be able to handle their substance use on their own**
  - Not ready to start treatment
  - Did not know where or how to get treatment
  - **Thought it would cost too much**
  - **Worried about what people would say or think if they got treatment**
  - **Not having enough time**
- Treatment disparities in access to treatment

SAMHSA, 2022

Substance Use Disorders

- In 2022, 46 million U.S. adults with a past year SUD
  - Almost 50% SUDS labeled as moderate to severe
  - Less than 25% received any treatment
- Top reasons for not getting treatment
  - Thought they should be able to handle their substance use on their own
  - Not ready to start treatment
  - Did not know where or how to get treatment
  - Thought it would cost too much
  - Worried about what people would say or think if they got treatment
  - Not having enough time
- **Treatment disparities in access to mental health treatment**

SAMHSA, 2022

Digital Therapeutics

- Managing, preventing, or treating a disorder
- Potential to mitigate economic, cultural, and geographic barriers to treatment

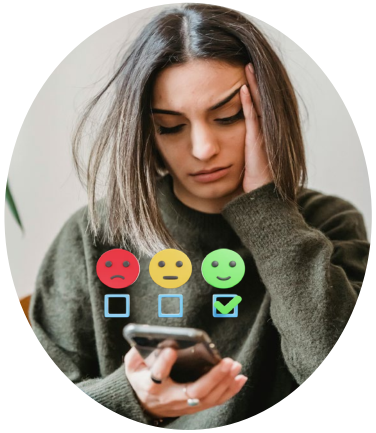
Smart Digital Therapeutics

- Personal sensing for monitoring
- Machine learning for prediction and explanation
- Detect fluctuations of risk in real time
- Make personalized recommendations
- Guide individuals to use the digital therapeutic more effectively

Personal Sensing

Personal sensing is a method of longitudinal measurement in situ. It uses smartphones and sensors embedded in the context of individuals' day-to-day lives.

Personal Sensing

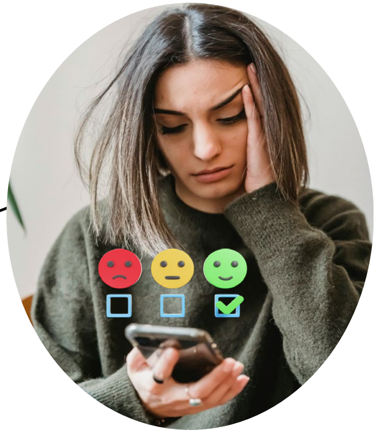


Ecological Momentary Assessment (EMA)

- Direct and frequent insight into subjective feelings and experiences
- Constructs easily map onto well-studied risk factors for lapse

Photo credits: liza summer; Cottonbro Studio; Mary Taylor (pexels.com)

Personal Sensing



Ecological Momentary Assessment (EMA)

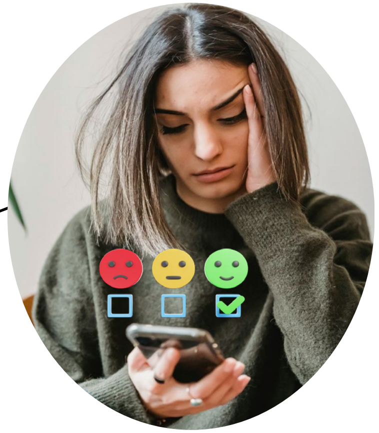
- Direct and frequent insight into subjective feelings and experiences
- Constructs easily map onto well-studied risk factors for lapse

Geolocation

- Passive sensing method
- Environmental contingencies

Photo credits: liza summer; Cottonbro Studio; Mary Taylor (pexels.com)

Personal Sensing



Ecological Momentary Assessment (EMA)

- Direct and frequent insight into subjective feelings and experiences
- Constructs easily map onto well-studied risk factors for lapse

Geolocation

- Passive sensing method
- Environmental contingencies

Cellular Communications

- Passive sensing method
- Metadata and text message content
- Provides unique insight into social circles and interaction

Photo credits: liza summer; Cottonbro Studio; Mary Taylor (pexels.com)

Personal Sensing

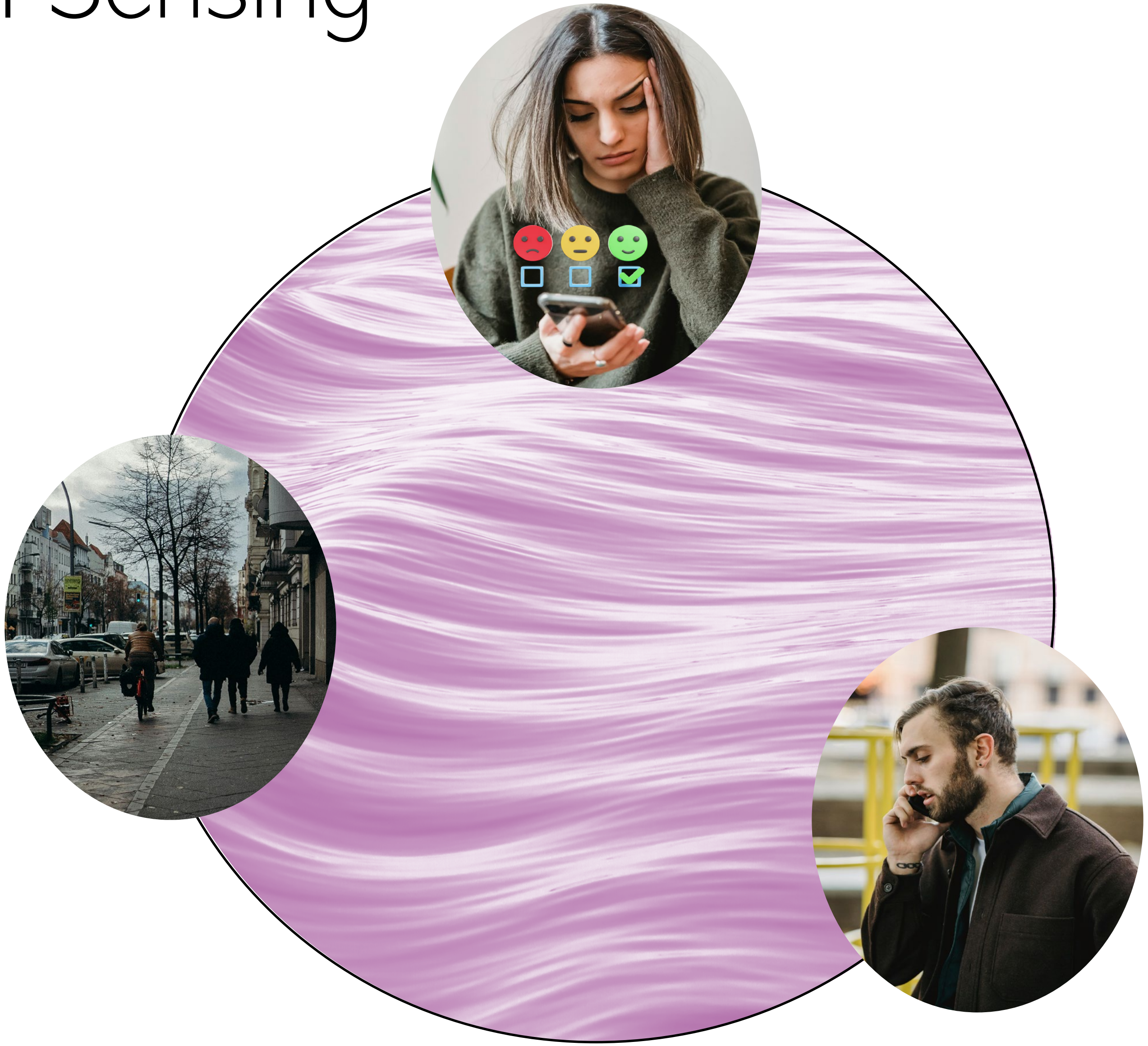


Photo credits: liza summer; Cottonbro Studio; Mary Taylor (pexels.com)

3 Research Questions

1. Is personal sensing acceptable to people with substance use disorders?

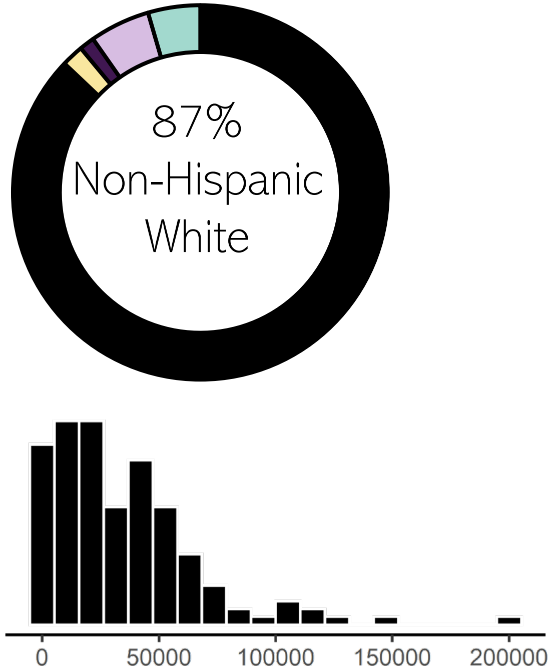
2. Can personal sensing data be used to predict lapses with high temporal precision?

3. How can the same models be used to inform clinical intervention?

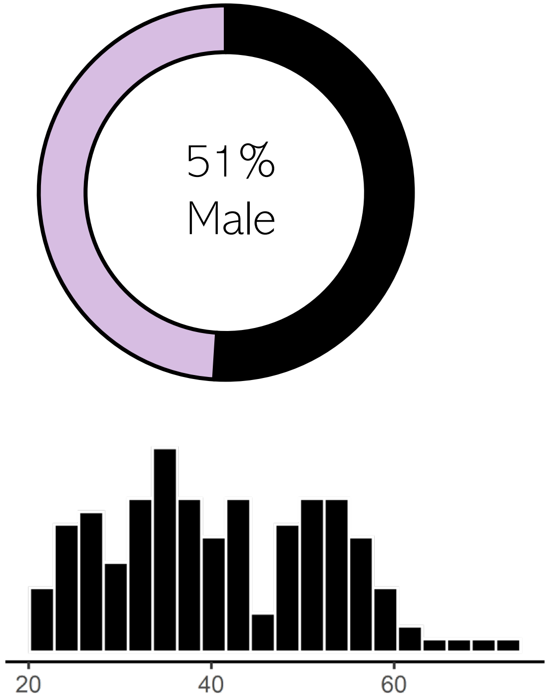
Participants

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

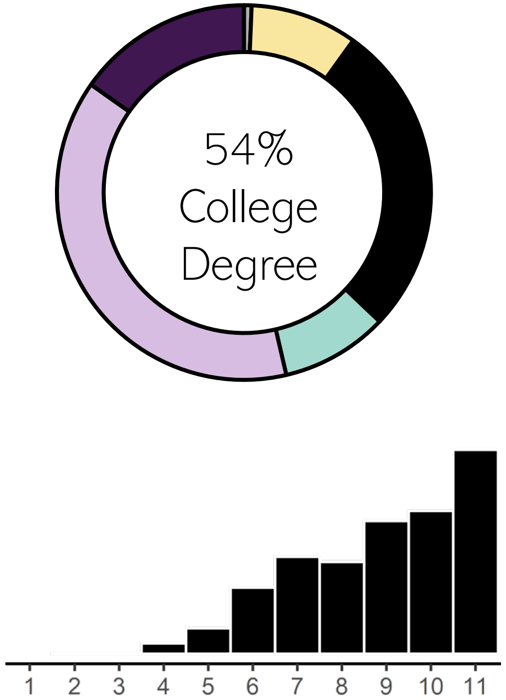
Participants



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 sensing data
  - 4x daily EMA

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

  - Geolocation
  - Cellular Communications (voice and text metadata and text message content)
  - Additional personal sensing measures were collected as part of the larger grant

3 Research Questions

1 Is personal sensing acceptable to people with substance use disorders?

2 Can personal sensing data be used to predict lapses with high temporal precision?

3 How can the same models be used to inform clinical intervention?

Original Paper

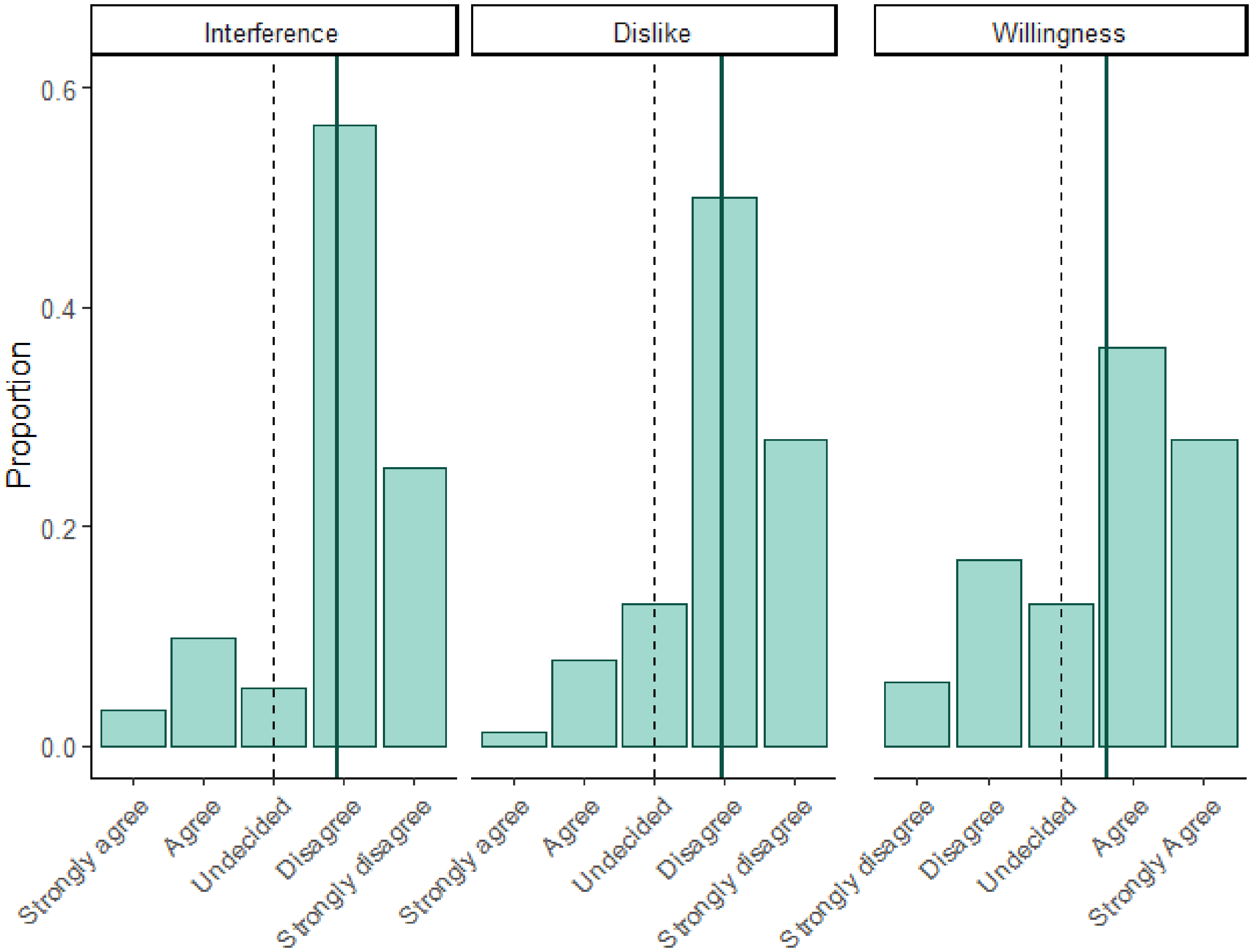
Acceptability of Personal Sensing Among People With Alcohol Use Disorder: Observational Study

Kendra Wyant, MS; Hannah Moshontz, PhD; Stephanie B Ward, MS; Gaylen E Fronk, MS; John J Curtin, PhD

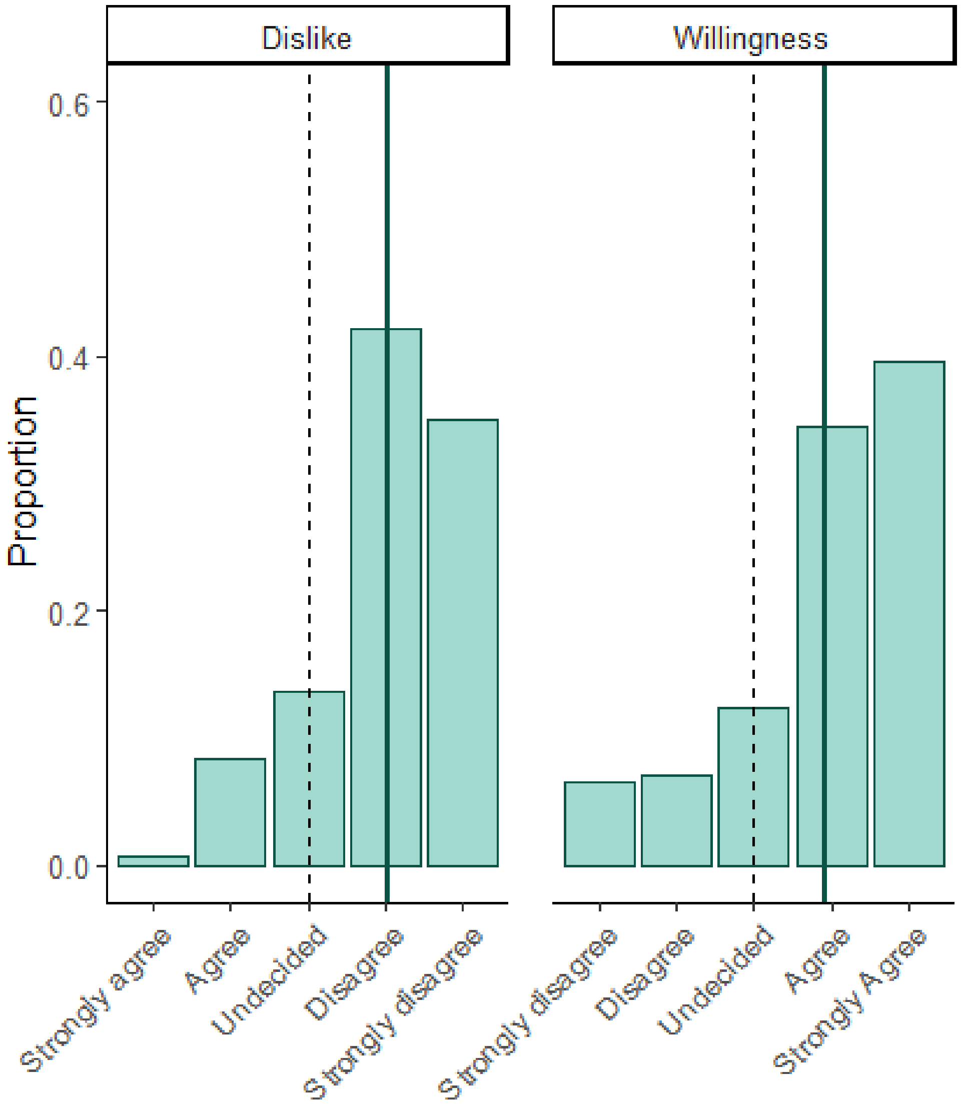
Department of Psychology, University of Wisconsin-Madison, Madison, WI, United States

Self-report Acceptability

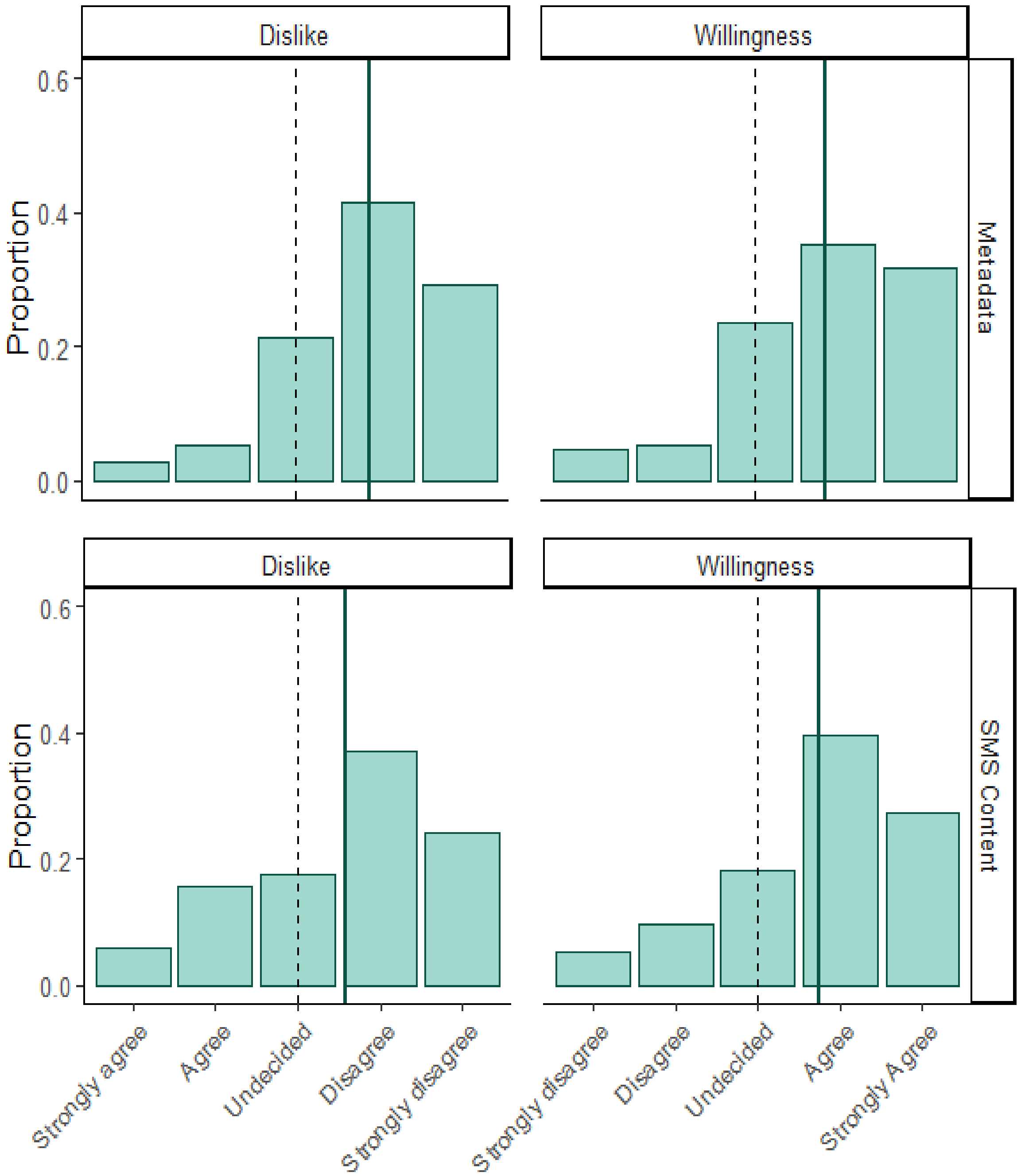
1. The daily surveys **interfered** with my daily activities.
2. I **disliked** the daily surveys.
3. I would be **willing** to complete the daily surveys for one year to help with my recovery.



Wyant et al., 2023



Wyant et al., 2023



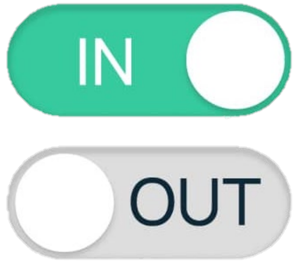
Wyant et al., 2023

Self-report Acceptability

- Average acceptability ratings were significantly above neutral midpoint.
- Majority of people reported:
  - 4x daily EMA did not interfere with their daily activities
  - They did not dislike any of the sensing methods
  - They would be willing to continue providing data for one year to help with their recovery
- Some people did self-report the personal sensing methods as unacceptable
  - But they still gave us data!

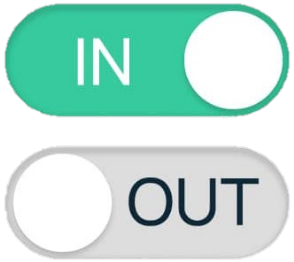
Behavioral Data

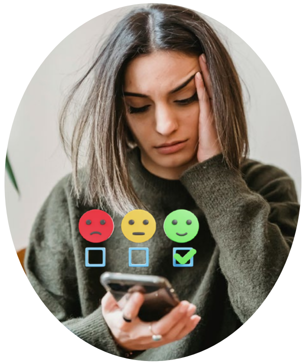
- Participants were required to opt-in to EMA
- Geolocation and Cellular communications were optional (mild incentive)
  - 100% opted in and provided some geolocation data
  - 99% opted in and provided us cellular communication logs



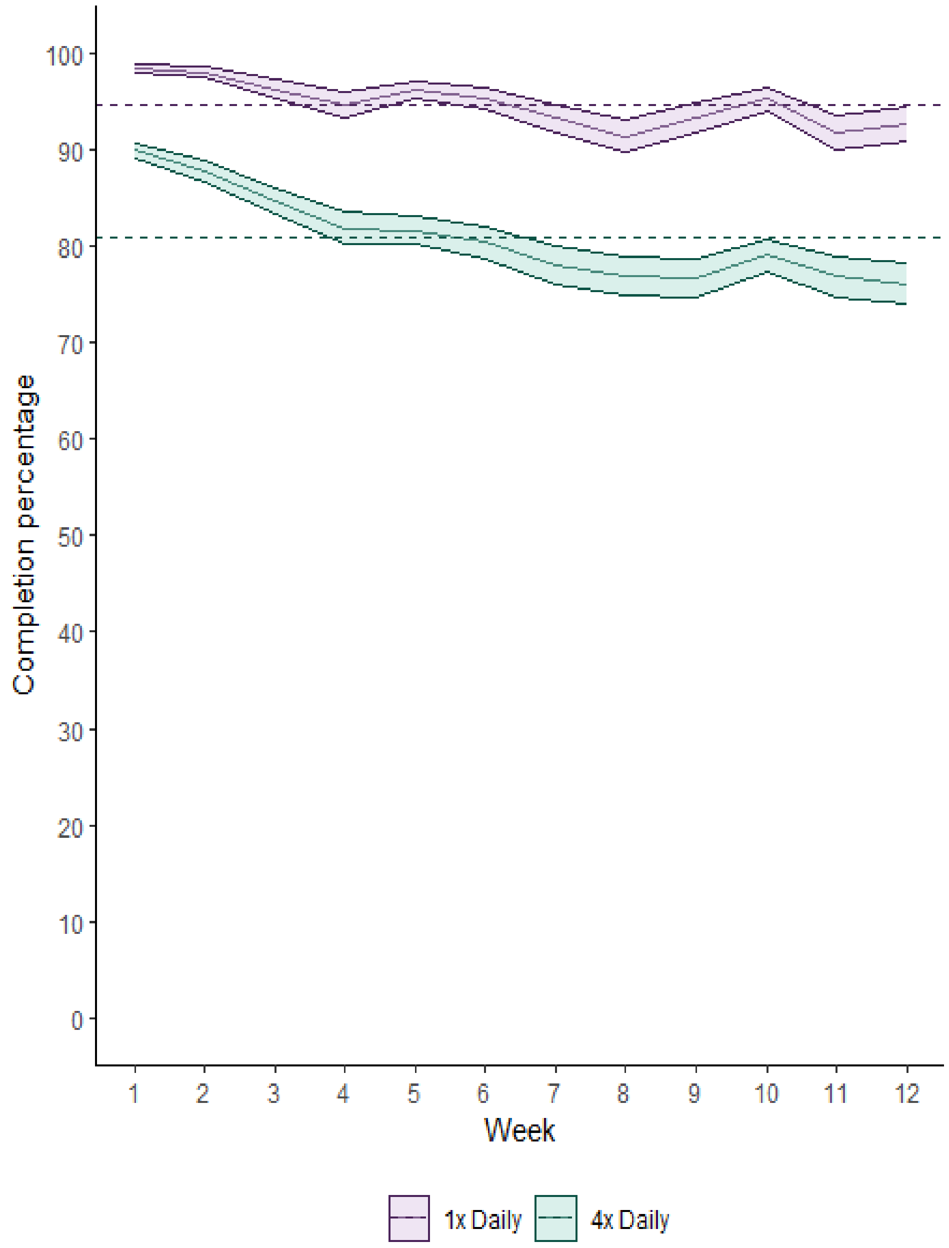
Behavioral Data

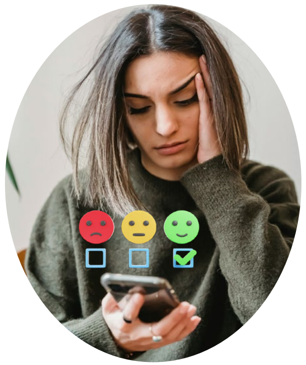
- Participants were required to opt-in to EMA
- Geolocation and Cellular communications were optional (mild incentive)
    - **100% opted in and provided some geolocation data**
    - 99% opted in and provided us cellular communication logs





Wyant et al., 2023





EMA completion percentage is high

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

Wyant et al., 2023

Behavioral Acceptability

- Almost everyone opted in to provide us with more sensitive data streams like geolocation and cellular communications
- People in early recovery can sustain the behaviors needed for our most effortful sensing method (4x daily EMA)

3 Research Questions

1 Is personal sensing acceptable to people with substance use disorders?

2 Can personal sensing data be used to predict lapses with high temporal precision?

3 How can the same models be used to inform clinical intervention?

3 Research Questions

1

Is personal sensing acceptable to people with substance use disorders?

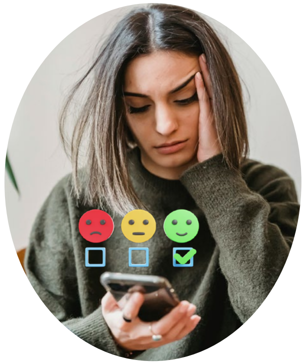
2

Can personal sensing data be used to predict lapses with high temporal precision?

3

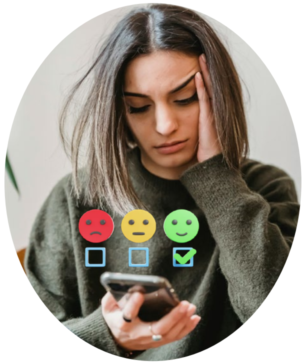
How can the same models be used to inform clinical intervention?

EMA



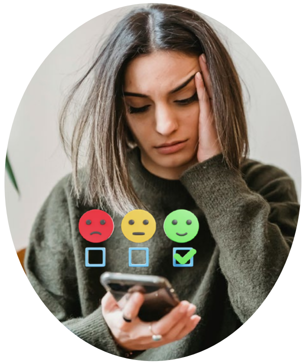
- Contains empirically supported constructs related to relapse prevention
- Appears acceptable
- **Use EMA to predict lapses in the next week, next day, and next hour**

Modeling Decisions

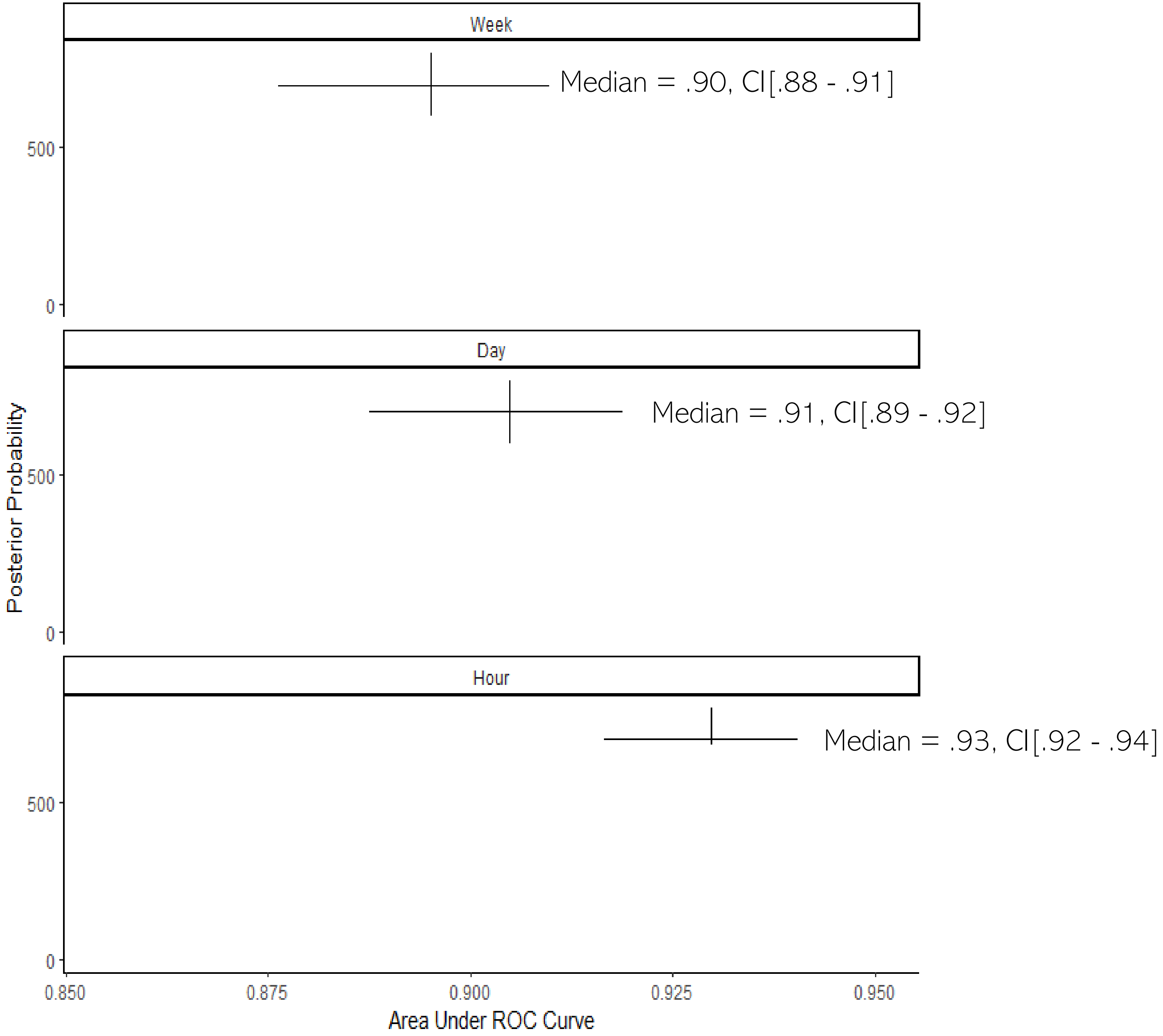


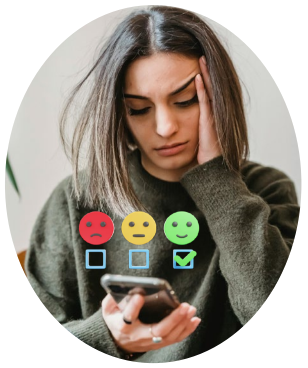
- Nested Grouped Cross Validation
- True prediction
- Hour level precision

Modeling Decisions

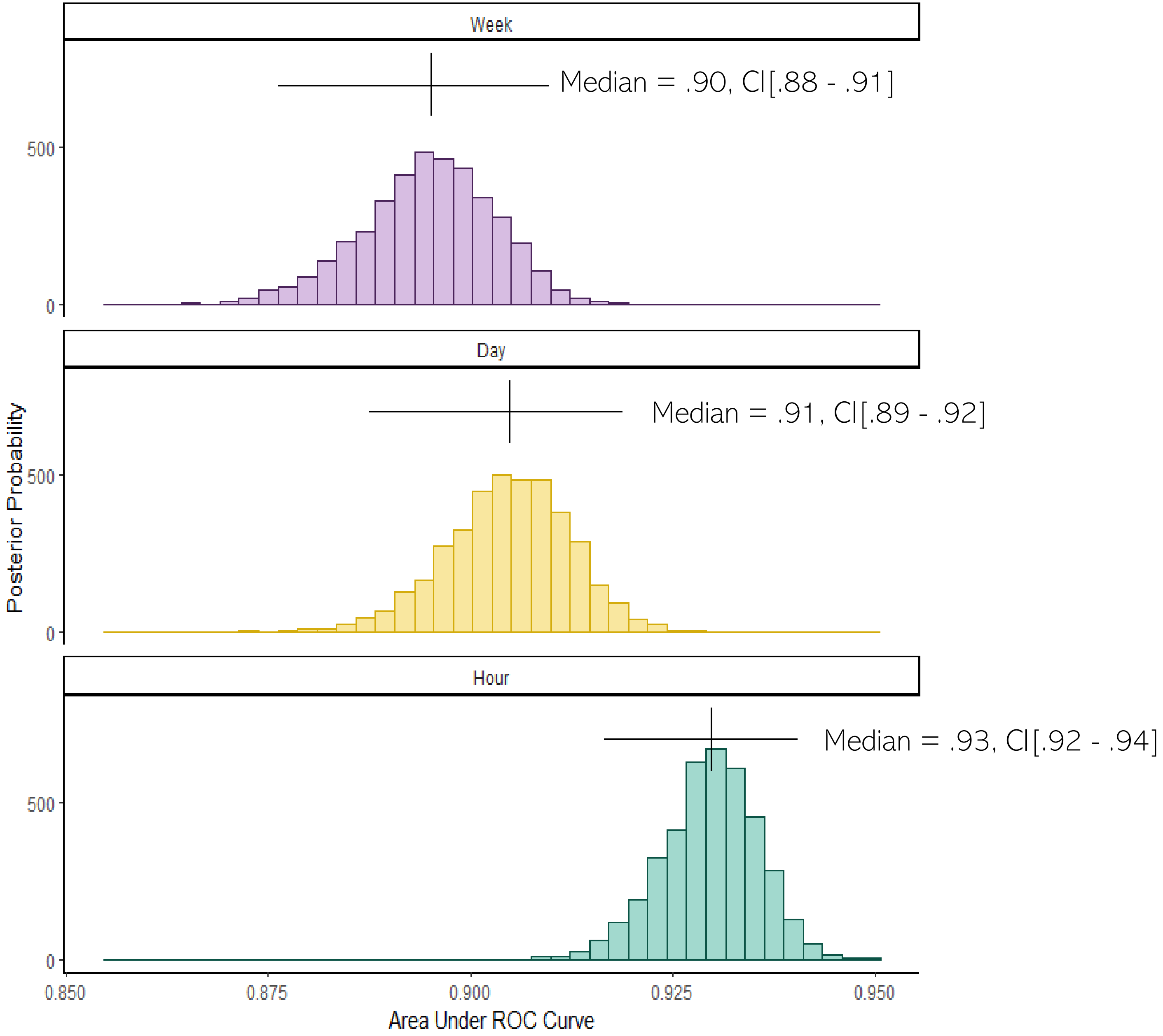


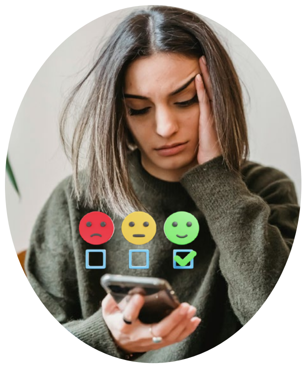
- Nested Grouped Cross Validation
- True prediction
- Hour level precision
- 286 features engineered from EMA, day and time of label, missing surveys, and demographics
- Area under the ROC curve (auROC)





Wyant & Sant'Ana et al., in press



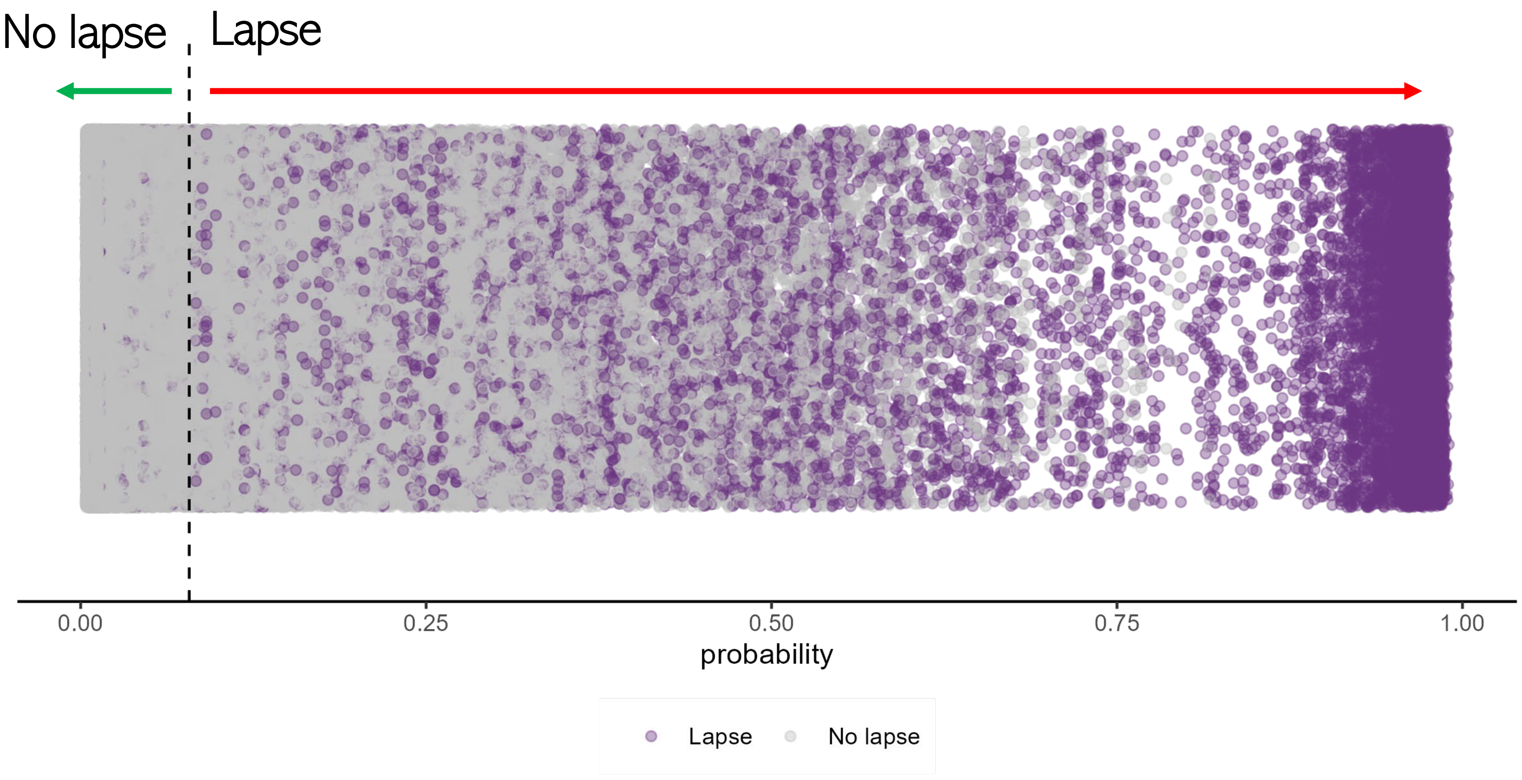


- We can predict hour by hour probabilities of lapse at varying levels of temporal precision with excellent performance
- Hour model performed significantly better than Day and Week model
- Day model performed significantly better than Week model

Wyant & Sant'Ana et al., in press

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 vs No lapse

		Truth	
		Lapse	No Lapse
Prediction	Lapse	17496	40912
	No Lapse	3611	212160

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

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

1 day model

Lapse vs No lapse

		Truth	
		Lapse	No Lapse
Prediction	Lapse	17496	40912
	No Lapse	3611	212160

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

J = .08; *N* = 274,179

1 day model

Lapse vs No lapse

		Truth	
		Lapse	No Lapse
Prediction	Lapse	17496	40912
	No Lapse	3611	212160

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

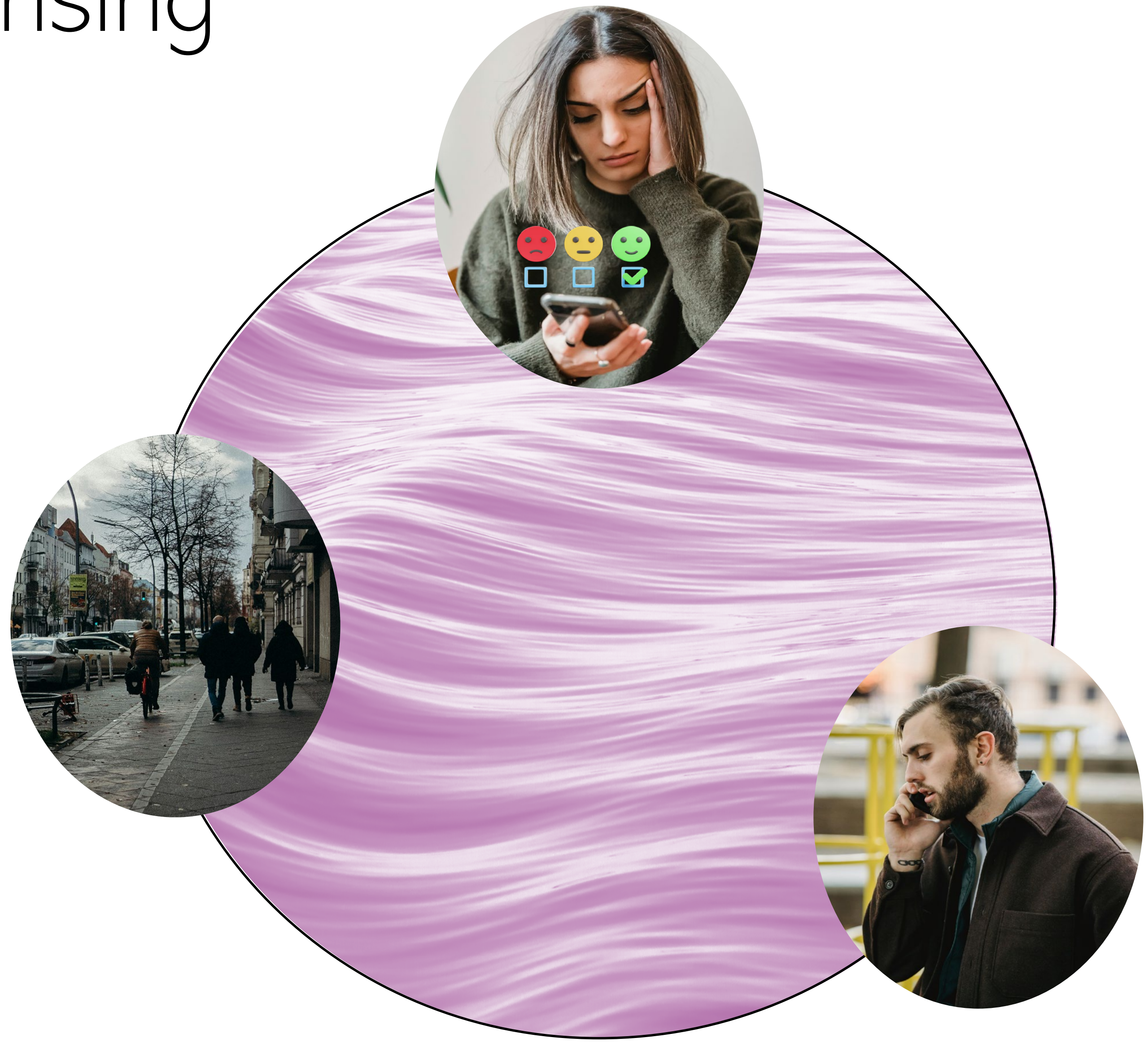
J = .08; N = 274,179

1 day model

Class Performance Metrics

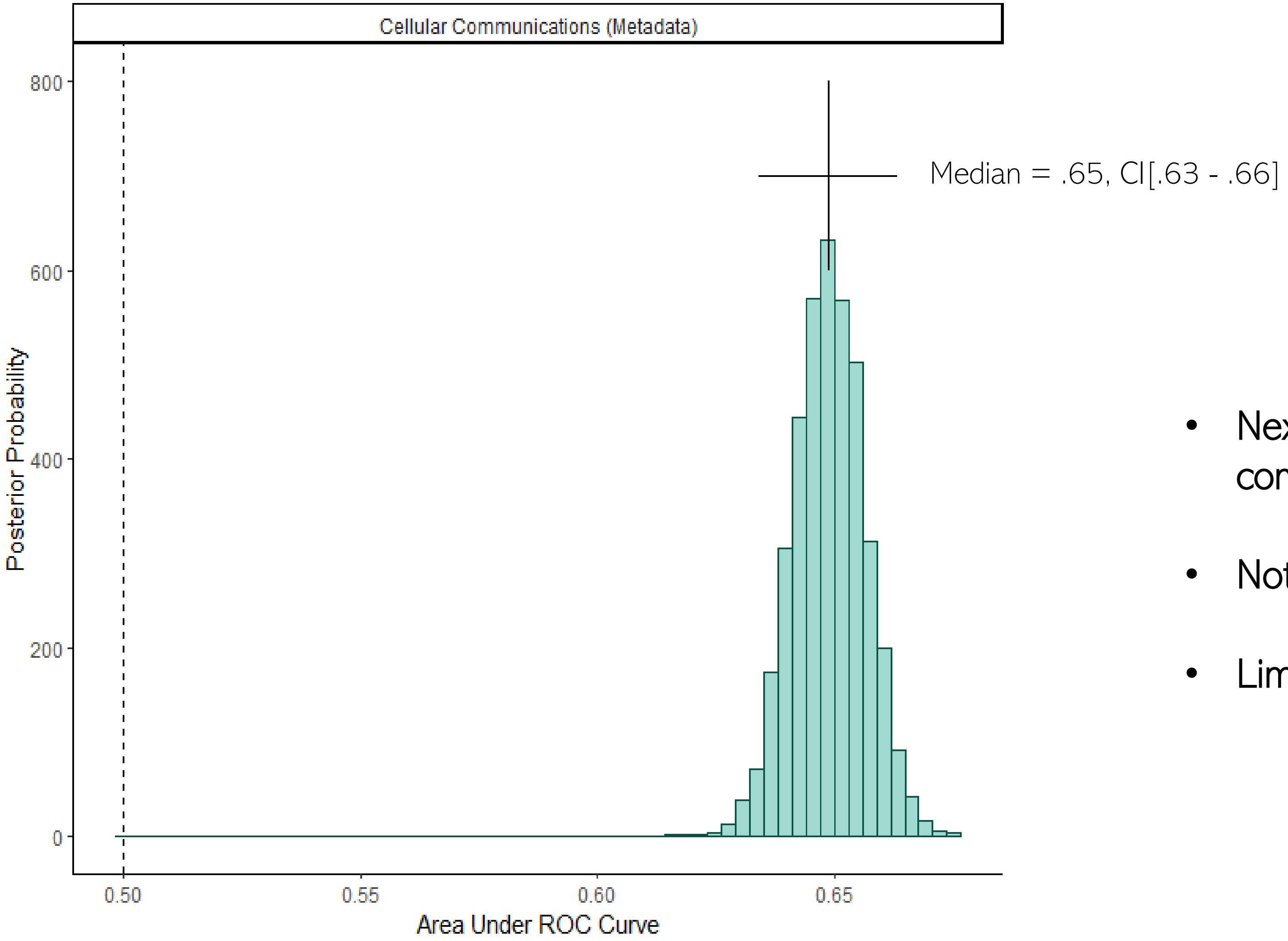
	Week	Day	Hour
Sensitivity	.82	.83	.86
Specificity	.82	.85	.88
Positive Predictive Value	.63	.30	.03
Negative Predictive Value	.94	.99	.99

Personal Sensing



Cellular Communications (Metadata)

- Most people use their smartphone to plan social outings, communicate with work associates and peers, and vent to the friends or loved ones
- Even with rise in popularity of social media and messaging apps, native voice calls and text messaging is still highly used
- Passive sensing methods may be particularly well-suited for more immediate just-in-time interventions
- Next hour predictions of lapse from features derived from voice and text message metadata



- Next hour prediction of lapses with cellular communications significantly higher than chance
- Not at a clinically useful level
- Limited to Metadata

Prediction window width = 1 hour

3 Research Questions

1 Is personal sensing acceptable to people with substance use disorders?

2 Can personal sensing data be used to predict lapses with high temporal precision?

3 How can the same models be used to inform clinical intervention?

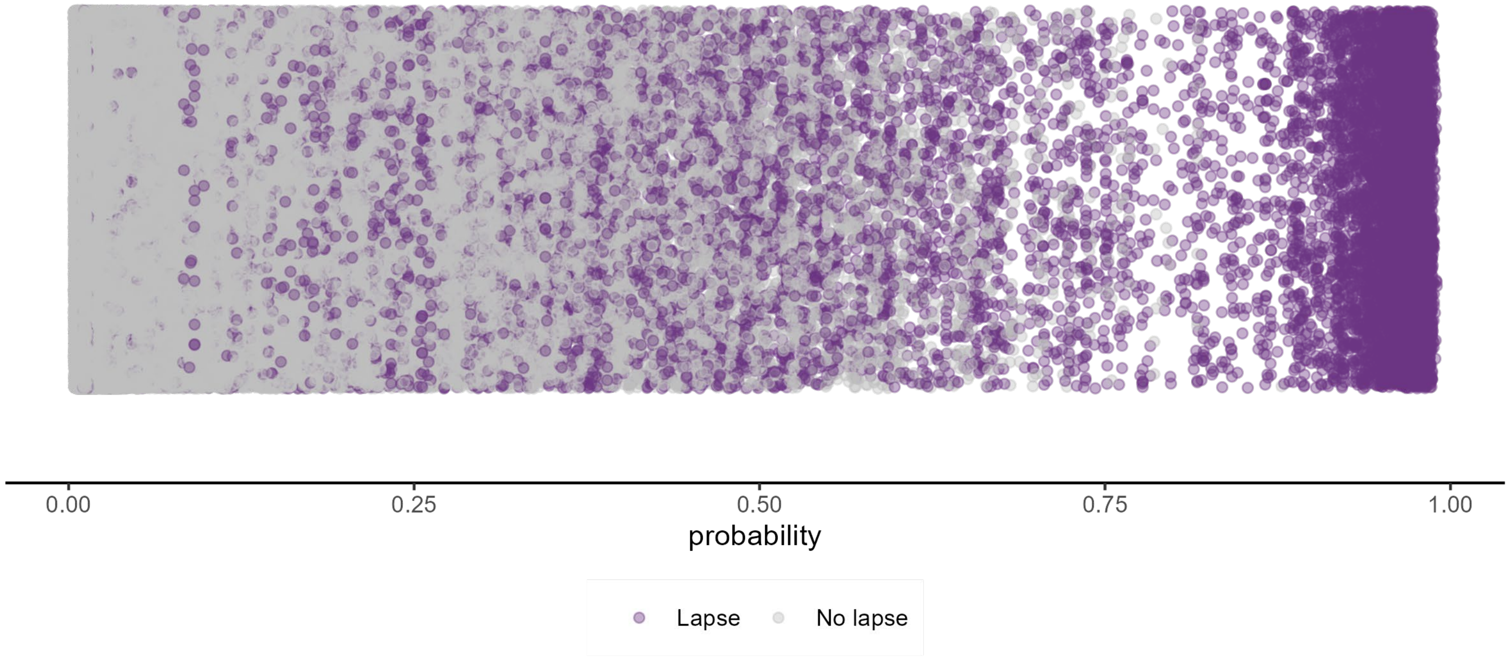
3 Research Questions

1 Is personal sensing acceptable to people with substance use disorders?

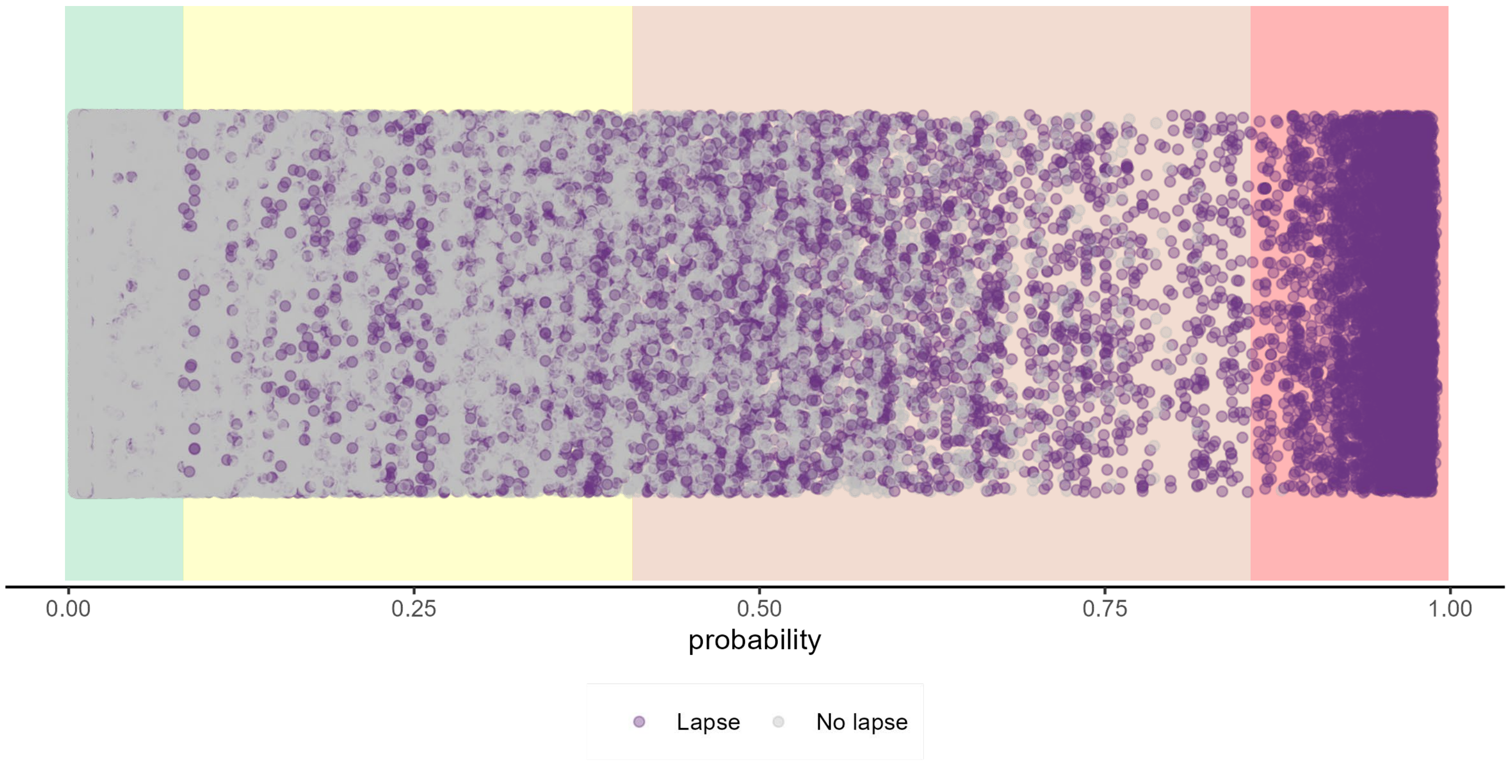
2 Can personal sensing data be used to predict lapses with high temporal precision?

3 How can the same models be used to inform clinical intervention?

Lapse Probabilities



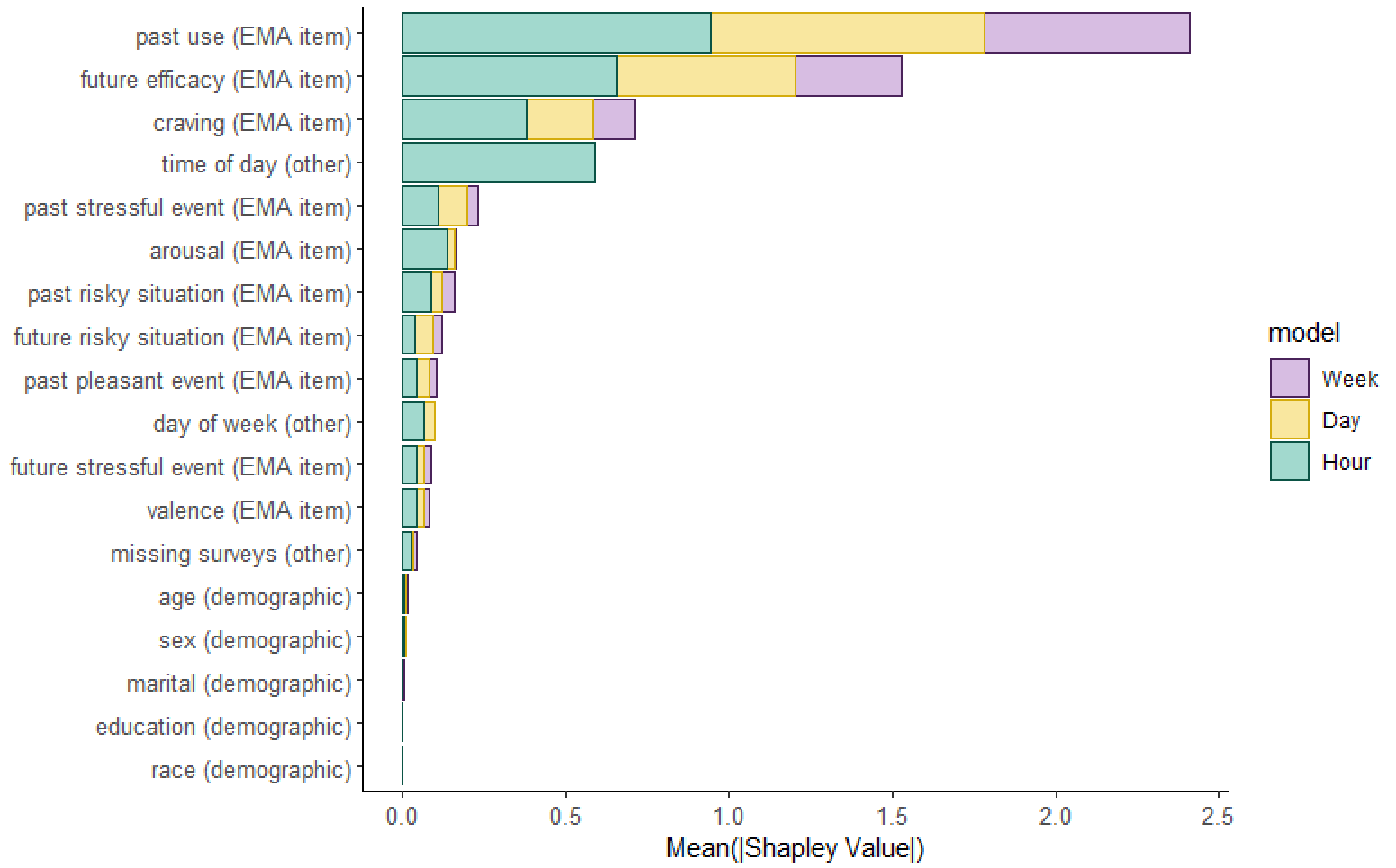
Lapse Probabilities

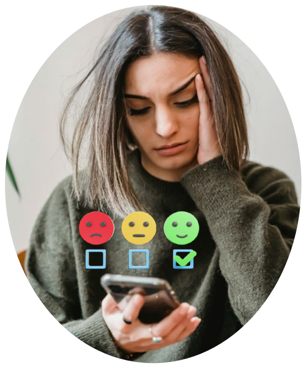


Treatments can be selected based on severity of risk

Feature Importance

- Treatments can be personalized based on relative top features contributing to the model's predictions
- **Global** feature importance tells us what features generally contributed most to our model's predictions across observations

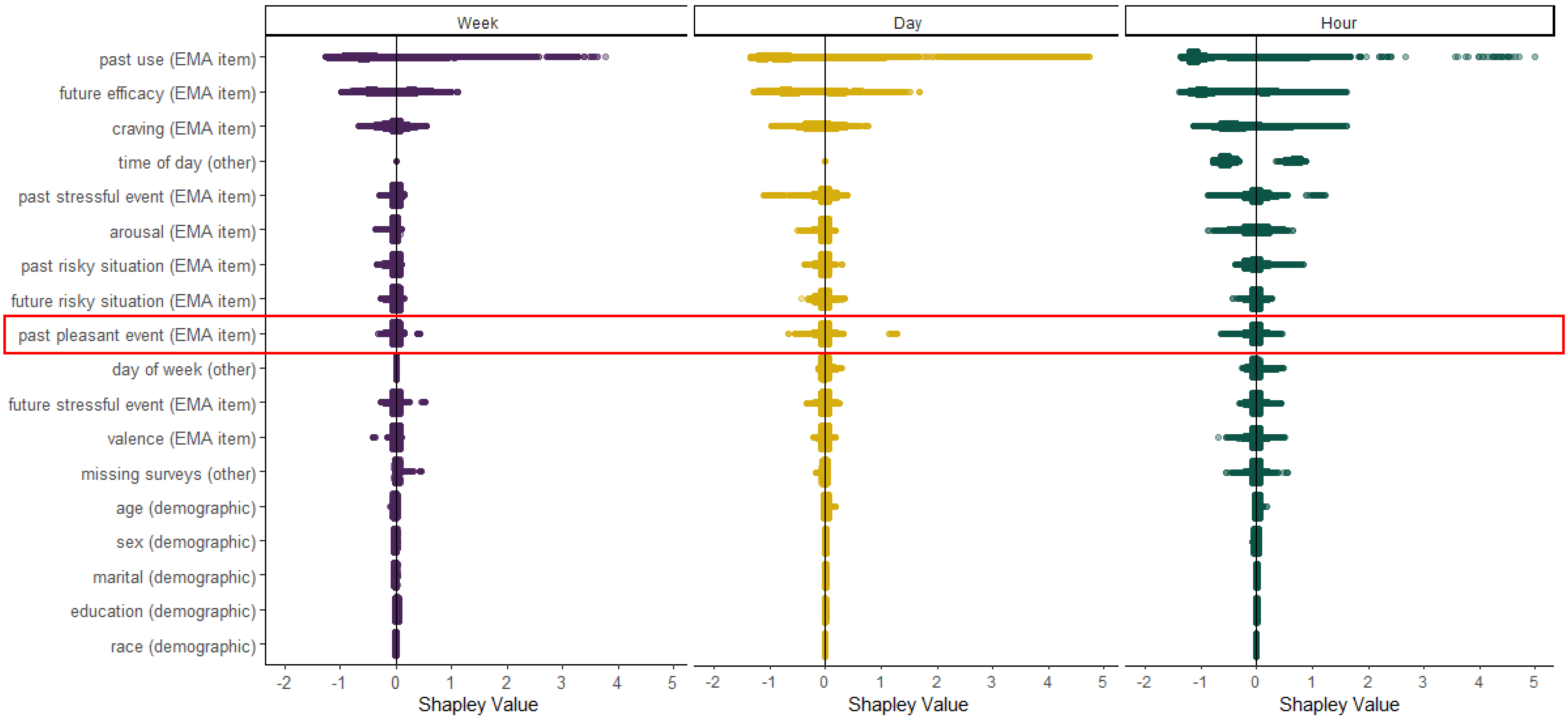




Wyant & Sant'Ana et al., in press

Feature Importance

- Treatments can be personalized based on relative top features contributing to the model's predictions
- **Global** feature importance tells us what features generally contributed most to our model's predictions across observations
- **Local** feature importance tells us which features were most important for a specific observation



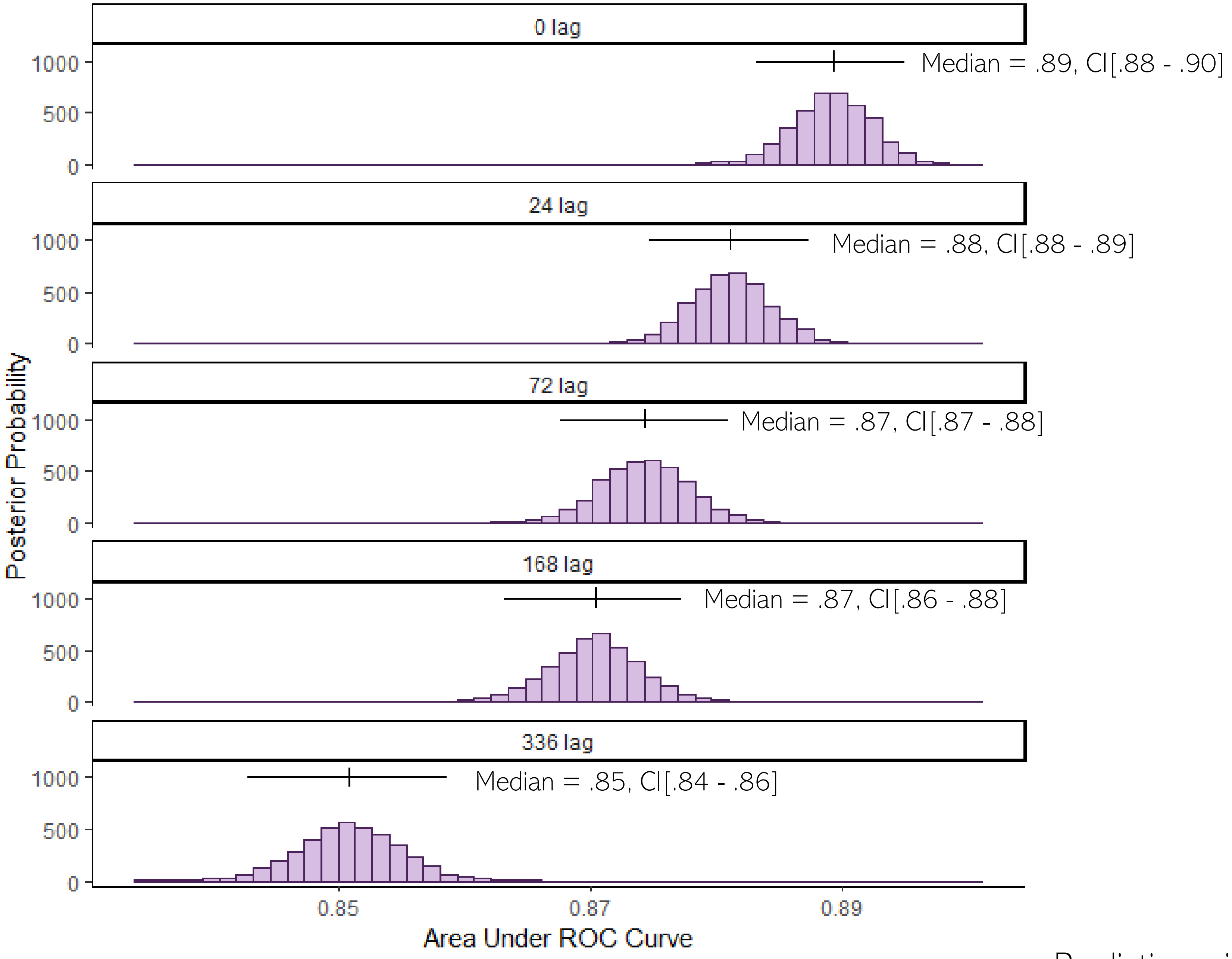
Wyant & Sant'Ana et al., in press

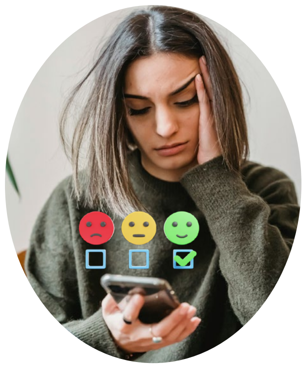


Photo credits: Kelvin Valerio; Sam Lion; Polina Zimmerman (pexels.com)

Lagged Lapse Predictions

- But some of these interventions take time to implement!
- 1 day, 3 days, 1 week, or 2 weeks into the future
- All compared to our baseline week model with no lag
- Model comparisons between adjacent lags to detect any significant degradation in performance





Prediction window width = 1 week

3 Research Questions

1 Is personal sensing acceptable to people with substance use disorders?

2 Can personal sensing data be used to predict lapses with high temporal precision?

3 How can the same models be used to inform clinical intervention?

Additional Future Directions

- Combining EMA with Geolocation
- Consider outcomes other than abstinence
- Experience with a different population
  - Diversity
  - Opioid Use Disorder
  - Up to one year

Photo credits: liza summer; Cottonbro Studio; Mary Taylor (pexels.com)

Acknowledgements

Research Mentor

John Curtin

Co-authors

Sarah Sant'Ana

Gaylen Fronk

Stephanie Ward

Hannah Moshontz

Addiction Research Center

Claire Punturieri

Coco Yu

Susan Wanta

Ariela Papp

Mentoring Committee

Kate Walsh

Mike Koenigs

Simon Goldberg

Linnea Burke

Addiction Research Center

UNIVERSITY OF WISCONSIN – MADISON

This research was supported by grants from the NIAAA (R01 AA024391; JJC) and the NIDA (R01 DA047315; JJC)

Acknowledgements

Cohort Support System

Brooke Sasia

Katie Pereira

Stephanie Ward