Personal Sensing in Clinical Research

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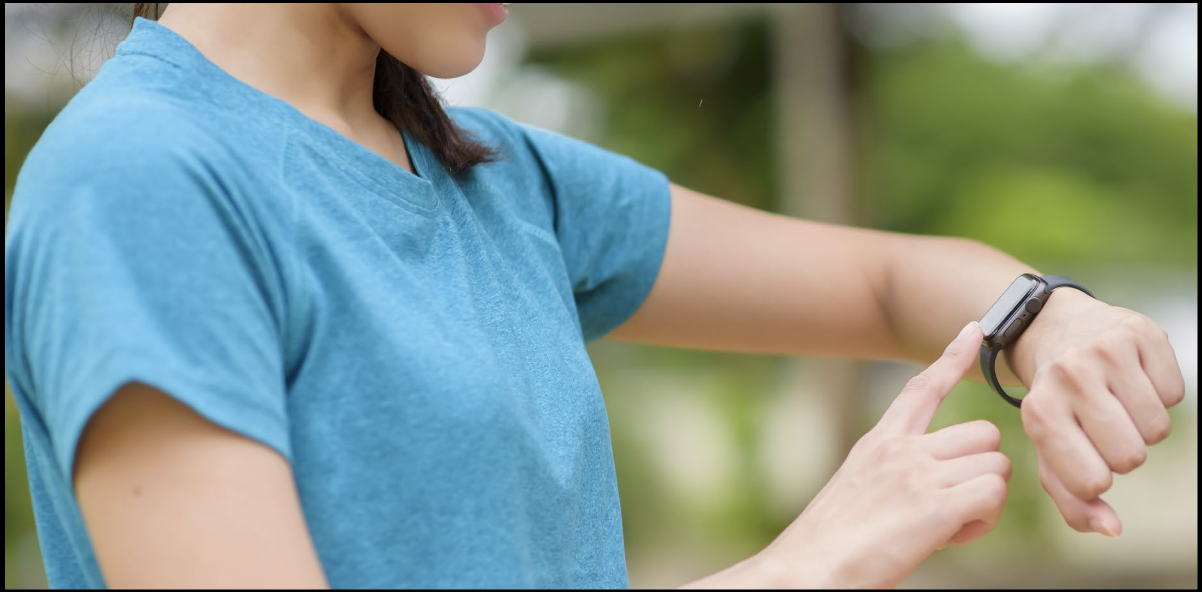


You
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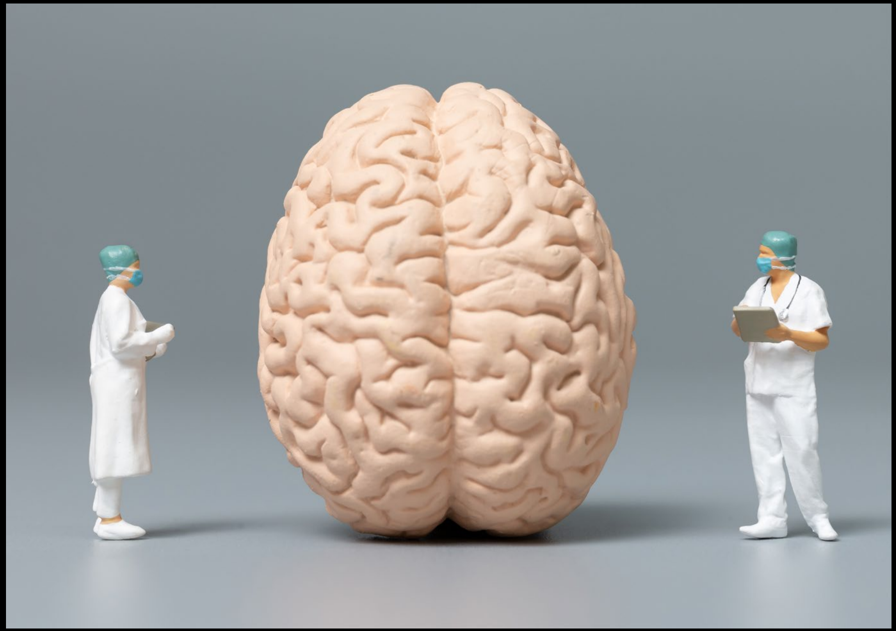
Personal Sensing and Mental Health

- Screening
  - Passive
  - Scalable

- Monitoring
  - Intervention prior to relapse

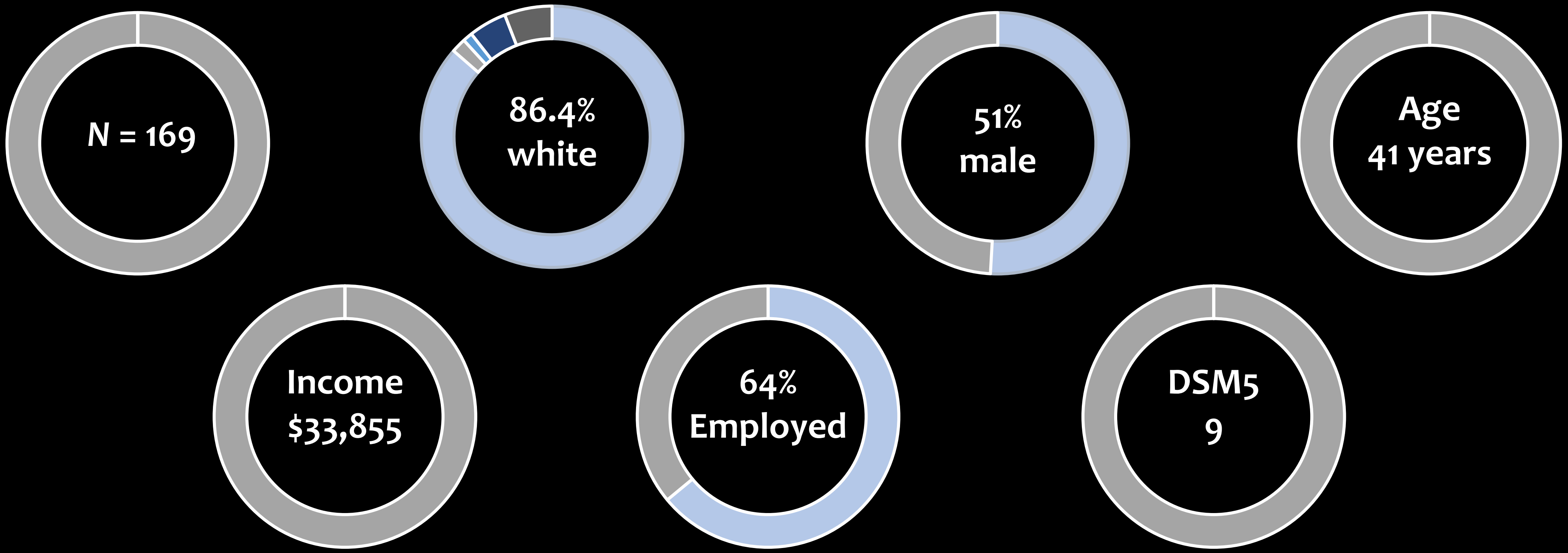


Alcohol Use Disorder (AUD)

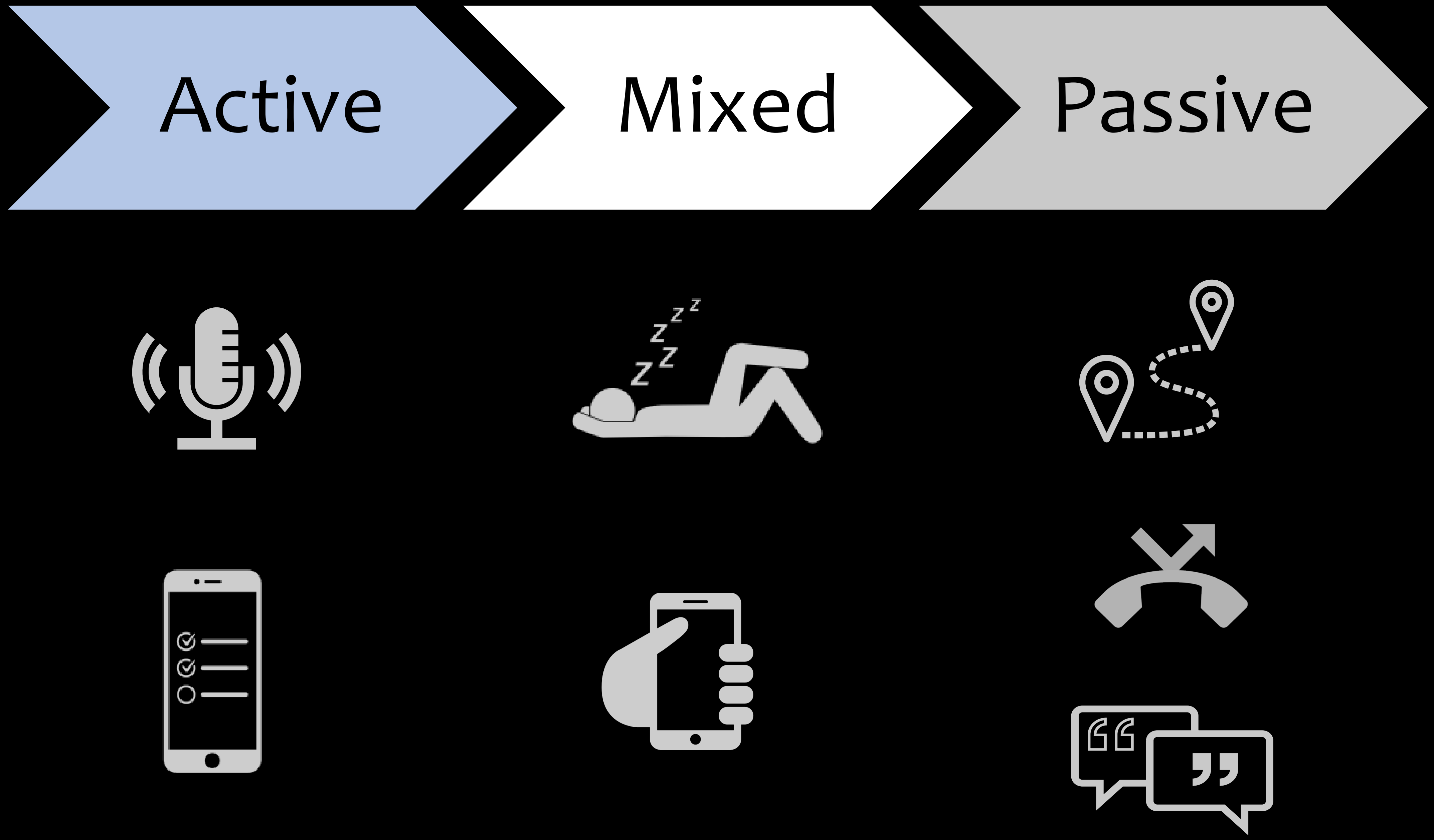
- AUD is a chronic relapsing disease
- Lapses are often early signs of relapse
- A temporally dynamic sensing system can capture day-to-day changes in lapse risk

Will people find these measures acceptable?

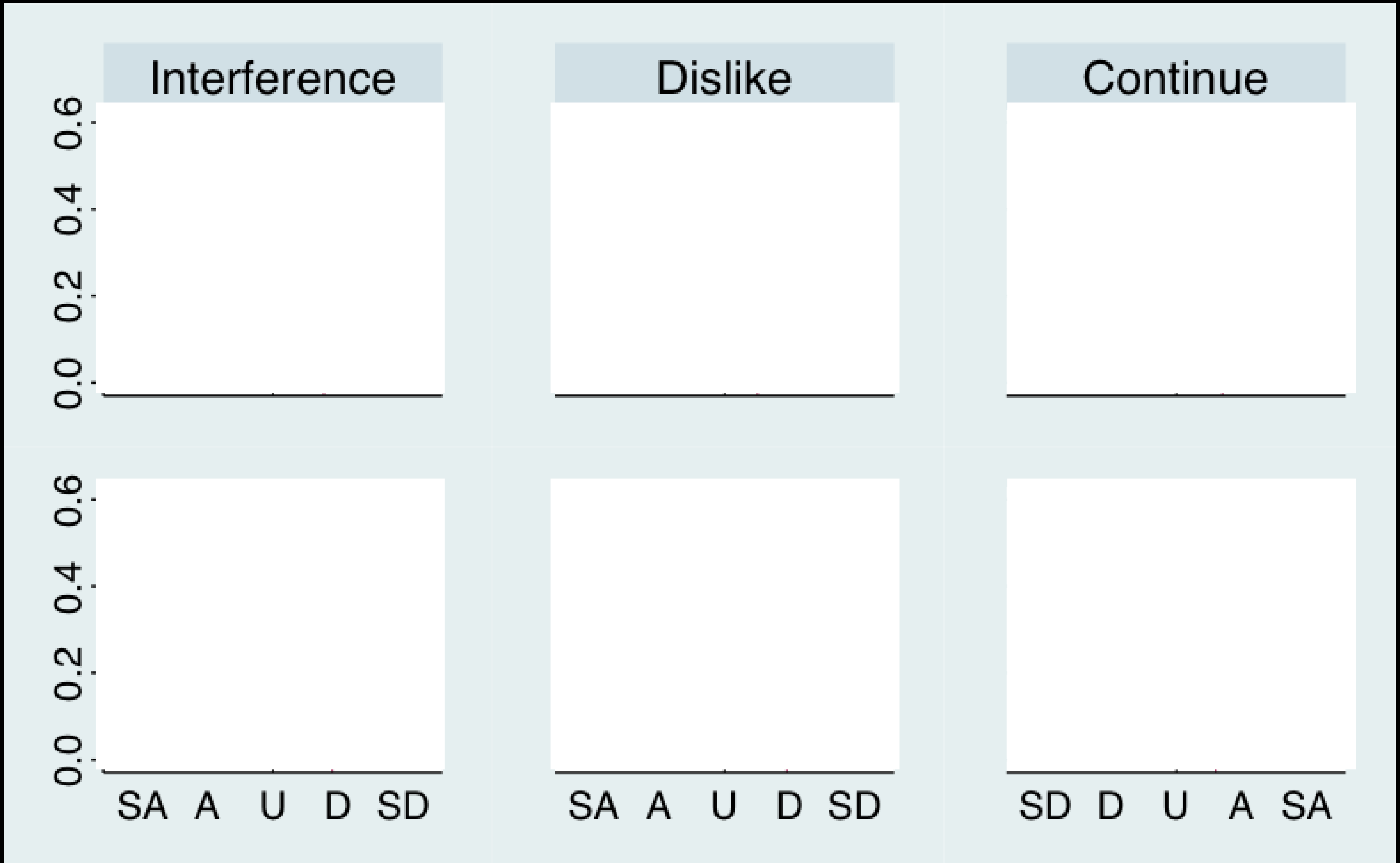
Sample Demographics




Active
Mixed
Passive


Active
Mixed
Passive

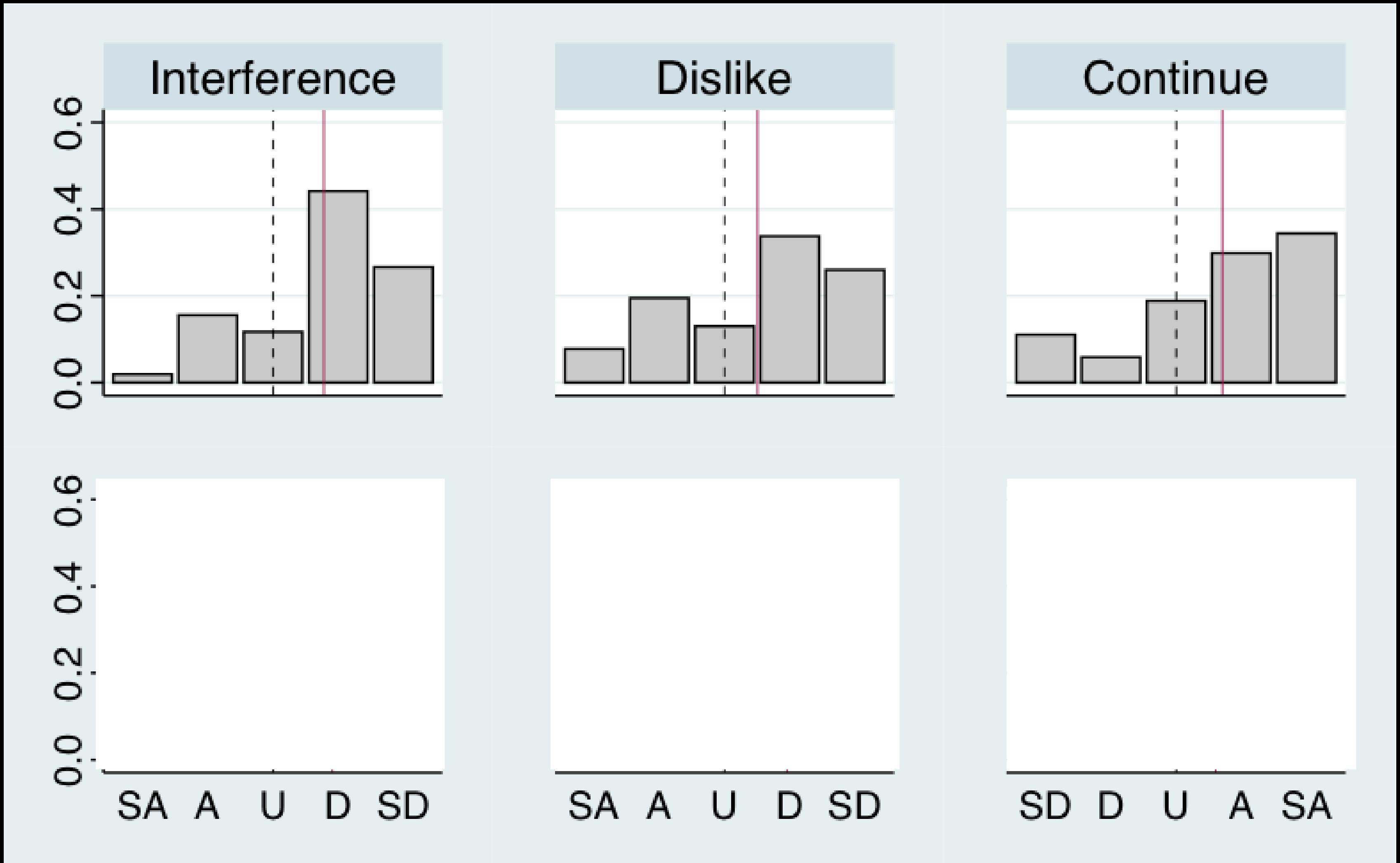
Active



Interference
Dislike
Continue
0.0
0.2
0.4
0.6
SA A U D SD
SA A U D SD
SD D U A SA

n = 154

Active



Interference
Dislike
Continue
0.0
0.2
0.4
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SA A U D SD
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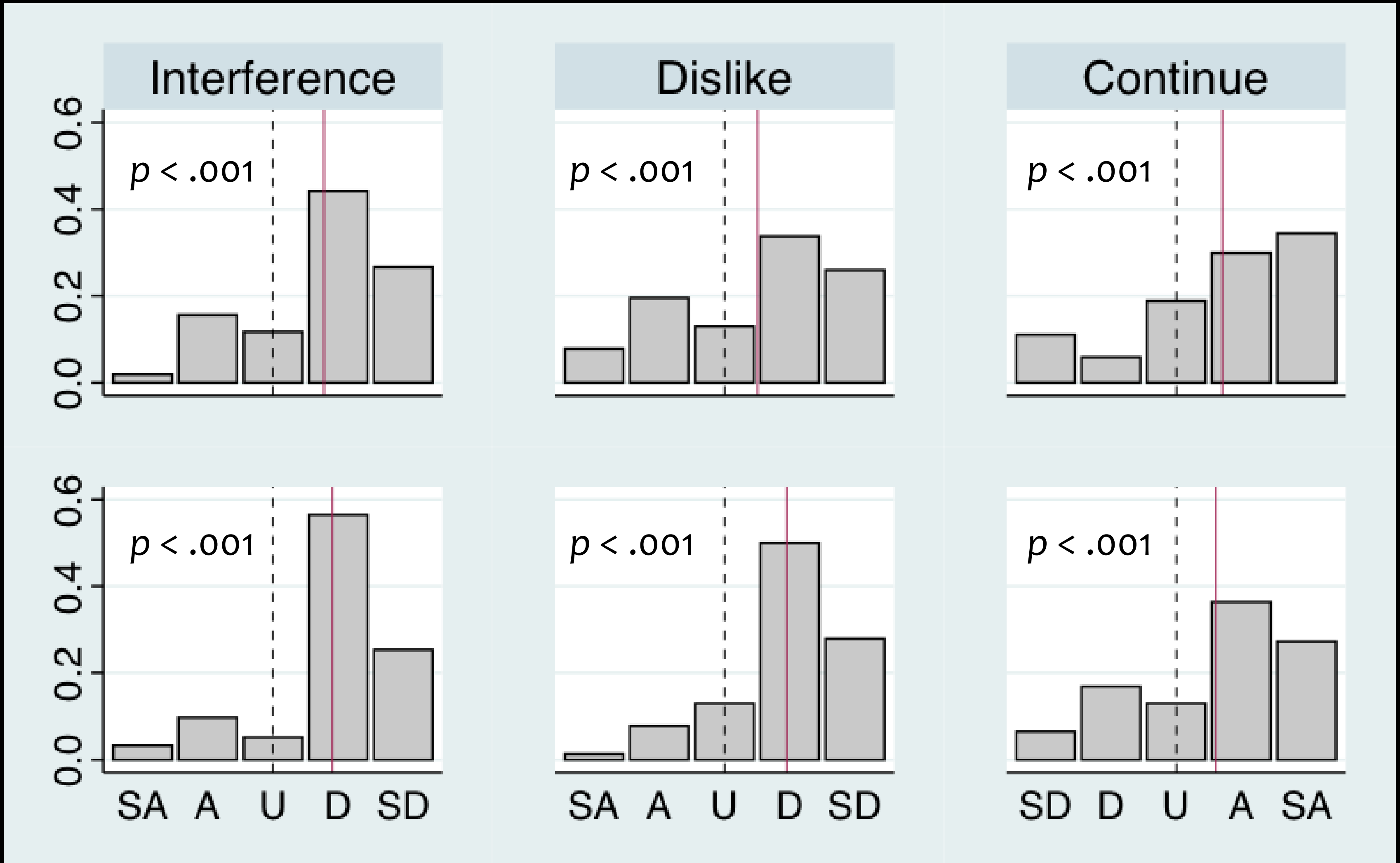
Active


Interference
Dislike
Continue
0.0
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p < .001
p < .001
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SA A U D SD
SA A U D SD
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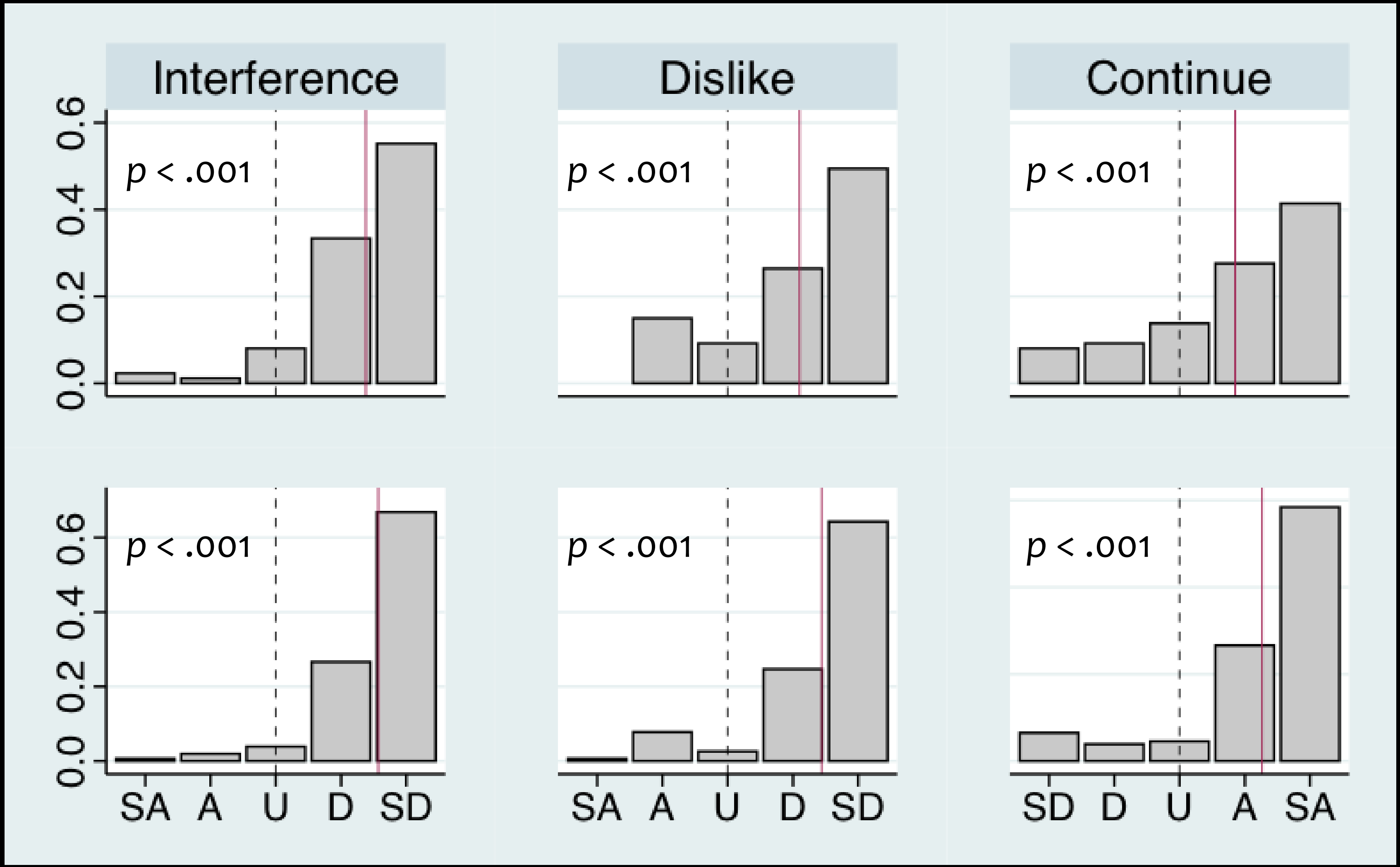
n = 154

Mixed



Interference
Dislike
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SA A U D SD
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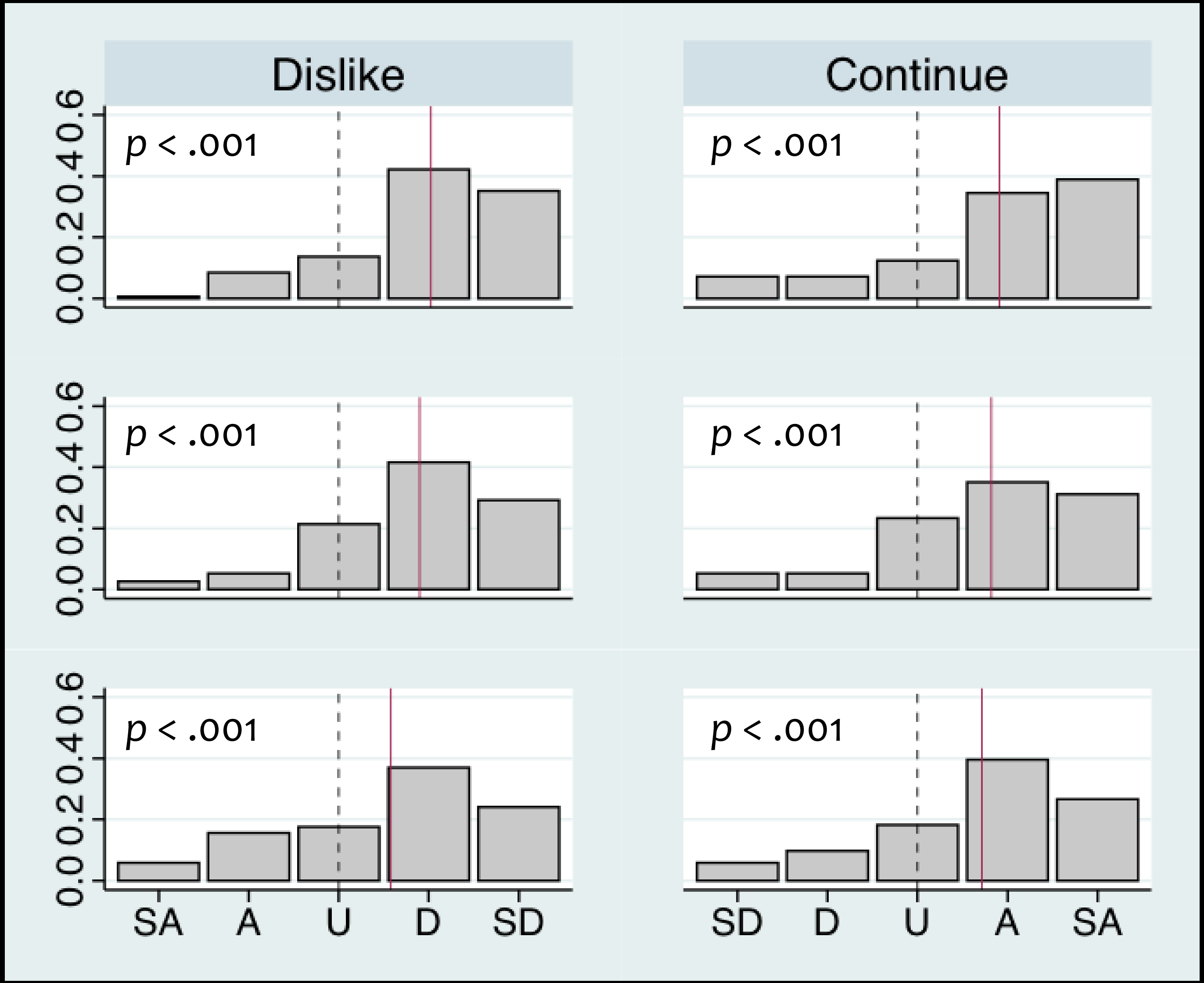
n = 154*

Passive



n = 154

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"This was my favorite part of the study. It helped me to set a good intention towards my recovery."

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"If I was more of a diary type of person I'd probably be more into this kind of thing. I mostly just didn't know what to say."

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“To be able to verbilize my feelings was the most best therapy.”

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“If I was more of a diary type of person I'd probably be more into this kind of thing. I mostly just didn't know what to say.”

“I felt like I needed to seek out a private spot to do the audio message. I would have much preferred to type the message.”

“It takes time out of your day where you have to completely switch locations just so you can do it in private. I don't like that people could hear me and the topic wherever and whenever so I stopped using it.”

"Never noticed so it was zero inconvenience whatsoever!"

"I went about my days as I normally would and never thought about it."

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"It is a huge invasion but my sobriety is paramount to my overall health."

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“It freaks me out that you can know everything I say. I sometimes say sensitive things.”

“It seems this was more to aid with the study research than to help with my recovery. If I could see a way it would be prioritized to help me, I would be more willing to have them tracked longer. “

Can we predict an alcohol lapse from cellular communication logs?

Cellular Communications

- Passive
- Widespread use
- Understudied personal sensing measure for AUD
- Promising signal of lapse risk


09:41
83%
Mom
iPhone
Remind Me
Message
ecline
Accept
7:15
J
Johnny
calling mobile...
mute
keypad
speaker
add call
FaceTime
contacts

Logs

- Phone number of other party
- Duration of call
- Date and time of message/call
- Type of message/call

How many contacts people communicate with each day.

Ratio of incoming to outgoing SMS messages.

A decline in number of outgoing calls.

Frequent communications with a new number.

An increase in outgoing messages on Friday and Saturday nights.

How many supportive contacts.

How many contacts in recovery.

Average level of pleasantness of interactions with contacts.

Ratio of drinking to non-drinking contacts.

How many drinkers in family.

Context

- Type of relationship
- Drank with contact in past
- Drinking status of contact
- Recovery status of contact
- Would drink in front of them
- Pleasantness of interactions
- Supportiveness


09:41
83%
Mom
iPhone
Remind Me
Message
Accept
7:15
Johnny
calling mobile...
mute
keypad
speaker
add call
FaceTime
contacts

Prediction Aims

Aim 1: Train and evaluate the best performing machine learning model to predict alcohol lapse from cellular communication logs and contextual information about the interactions

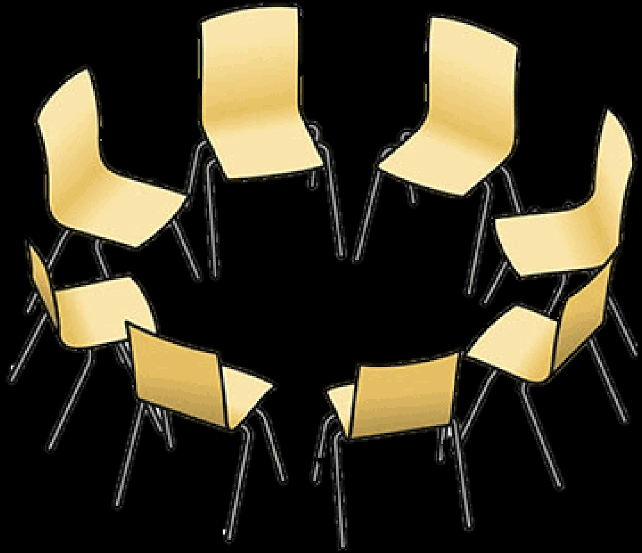
Prediction Aims

Aim 1: Train and evaluate the best performing machine learning model to predict alcohol lapse from cellular communication data and contextual information about the interactions

Aim 2: Employ a model comparison approach to compare models that use all available features with models that are restricted to only passive signals

Explanation Aim

Aim 3: Evaluate the importance of feature sets within the top performing model to inform treatment



Clinical Significance

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Images

- https://www.google.com/url?sa=i&url=https%3A%2F%2Feconsultancy.com%2Fwhat-is-social-media-here-are-34-definitions%2F&psig=AOvVaw2CTHW2qy4qeCwi6an-GkXJ&ust=1617384698085000&source=images&cd=vfe&ved=0CA0QjhxqFwoTCMC-3tfJ3e8CFQAAAAAdAAAAABAV
- Vecteezy images
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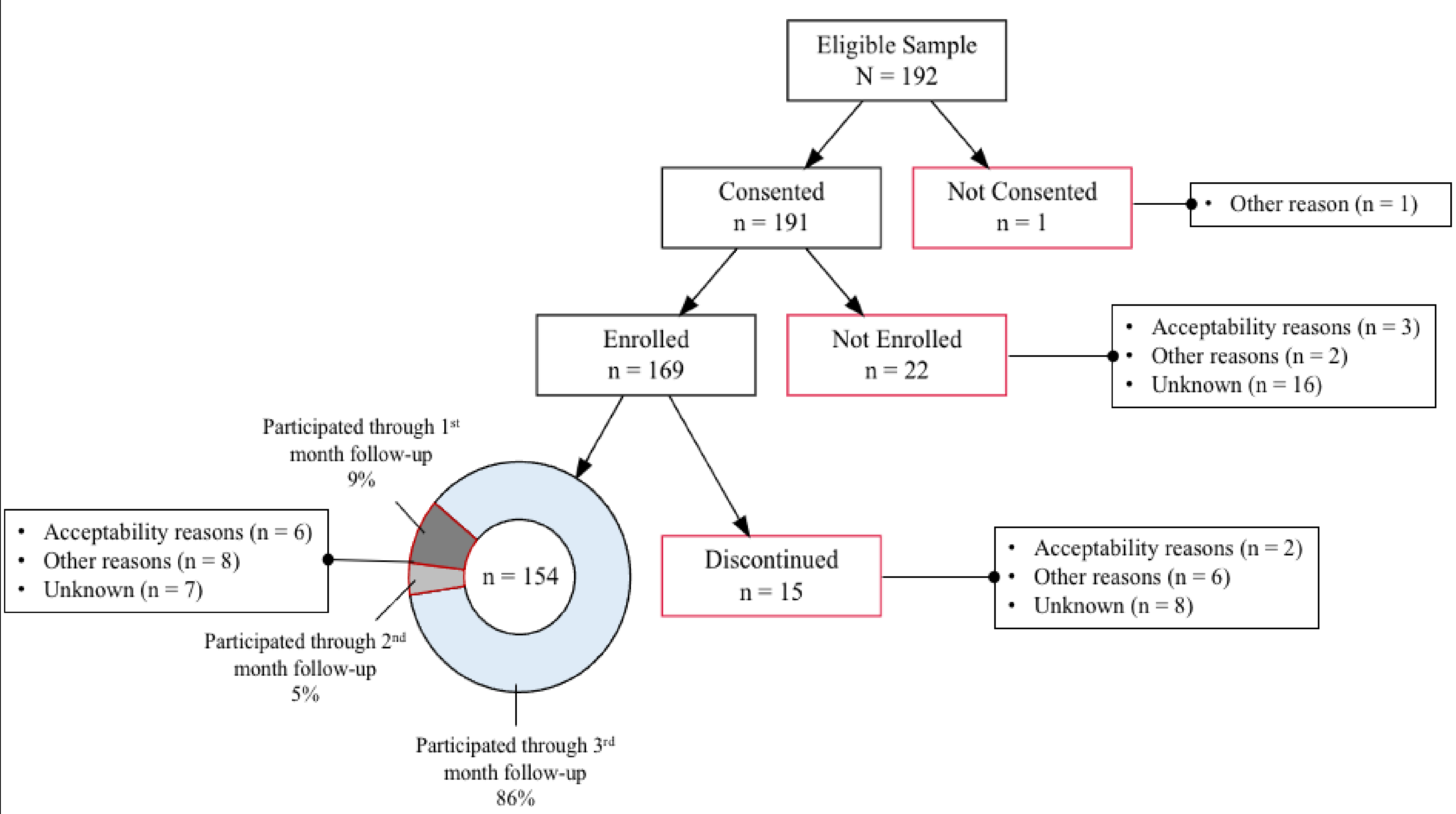
- https://www.iup.edu/counselingcenter/services/groups-for-iup-students/

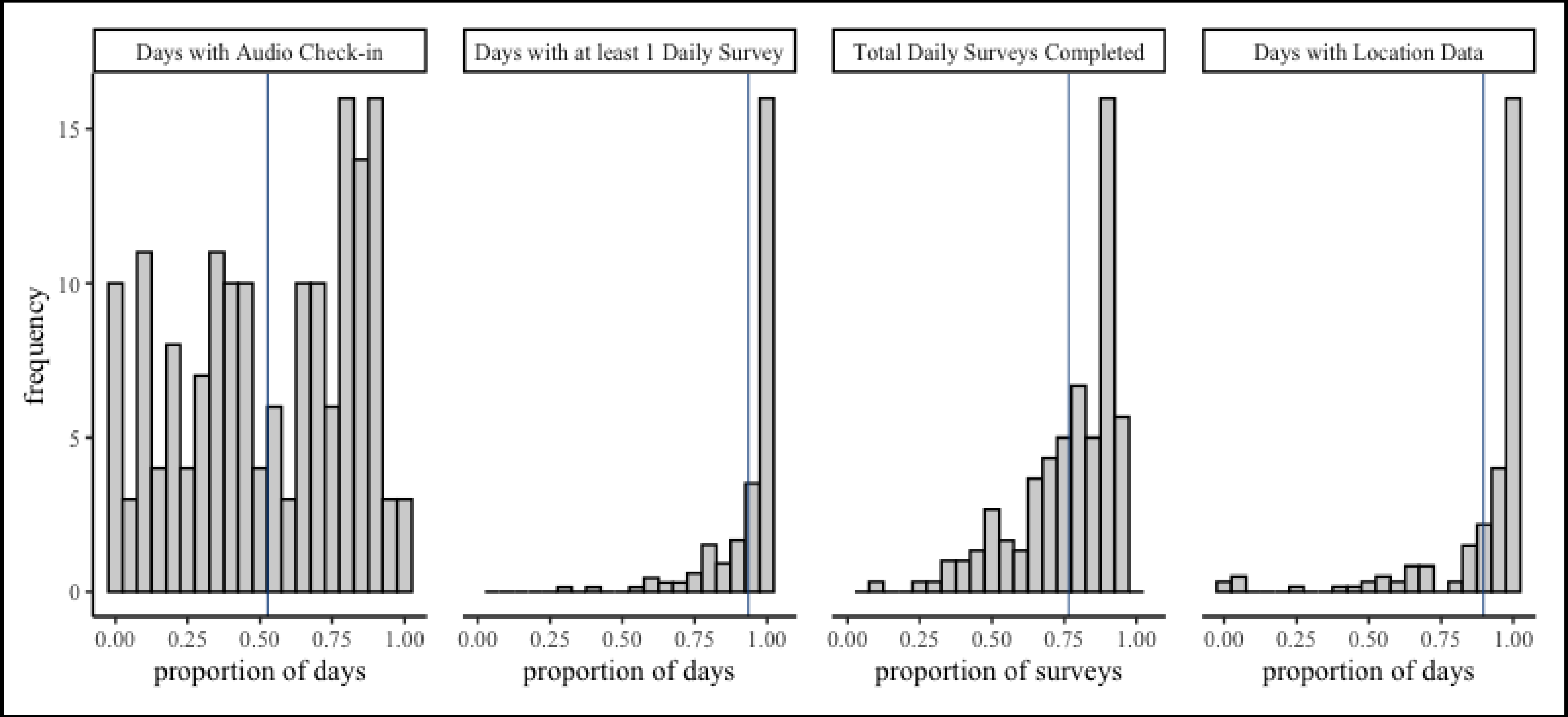
Thank You!

Questions?

Thoughts?



Eligible Sample
N = 192
Consented
n = 191
Not Consented
n = 1
• Other reason (n = 1)
Enrolled
n = 169
Not Enrolled
n = 22
• Acceptability reasons (n = 3)
• Other reasons (n = 2)
• Unknown (n = 16)
Participated through 1st month follow-up
9%
• Acceptability reasons (n = 6)
• Other reasons (n = 8)
• Unknown (n = 7)
n = 154
Participated through 2nd month follow-up
5%
Participated through 3rd month follow-up
86%
Discontinued
n = 15
• Acceptability reasons (n = 2)
• Other reasons (n = 6)
• Unknown (n = 8)



Days with Audio Check-in
Days with at least 1 Daily Survey
Total Daily Surveys Completed
Days with Location Data
frequency
15
10
5
0
0.00
0.25
0.50
0.75
1.00
proportion of days
proportion of days
proportion of surveys
proportion of days

Demographics for enrolled participants (N = 169)

	n	%	M	SD
Age			40.5	12.1
Sex				
Female	83	49.1		
Male	86	50.9		
Race				
American Indian/Alaska Native	3	1.8		
Asian	2	1.2		
Black/African American	8	4.7		
White	146	86.4		
Multiracial or not listed	10	5.9		
Hispanic, Latino, or Spanish Origin				
Yes	5	3.0		
No	164	97.0		
Income			33855	31311
Marital Status				
Never married	78	46.2		
Married	35	20.7		
Divorced	48	28.4		
Separated	6	3.6		
Widowed	2	1.2		

Why Machine Learning?

- Well suited for handling the complexities of AUD and diversity across individuals
- Can fit many models without risk of overfitting because the models are evaluated on new data (i.e., validation and test set)
- Feature engineering
- Can be used for both prediction and explanation

Log Type	Measure
SMS	Phone number of the other party
	Date message was received
	Date message was sent
	Message type (incoming, outgoing, draft)
	Contact saved in phone
	Read status (read, unread)
Call	Phone number of the other party
	Date of call
	Call type (incoming, outgoing, missed, voicemail, rejected, blocked)
	Facetime (iPhone only)
	Call duration (in seconds)
	Contact saved in phone
	Caller ID (allowed, restricted, unknown, payphone)