A Personal Sensing Approach to Alcohol Lapse Prediction

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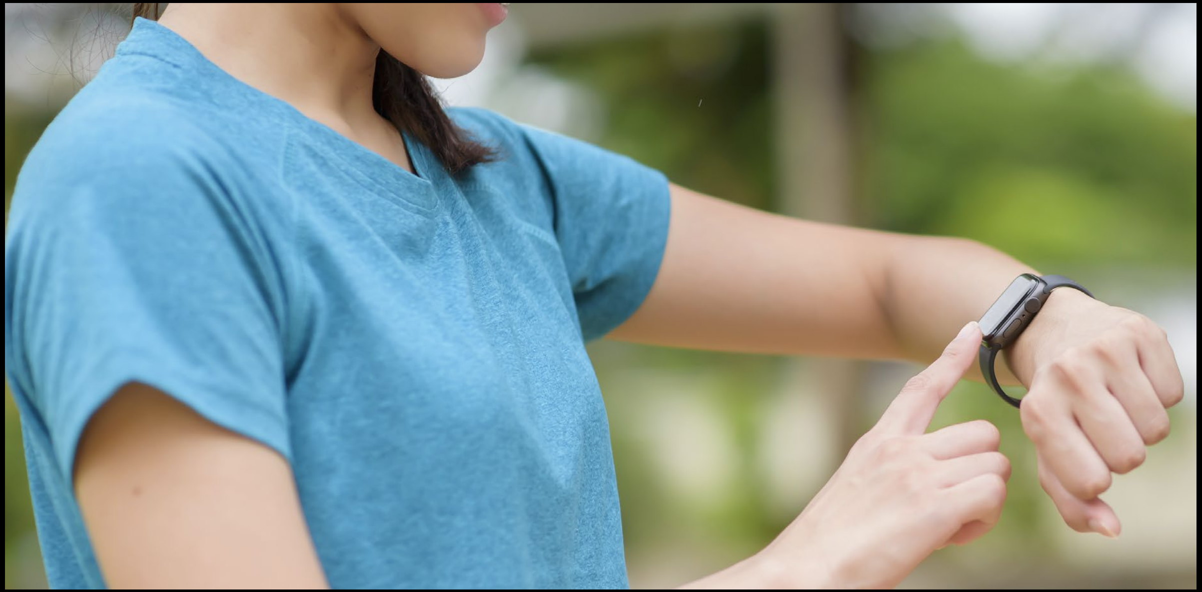
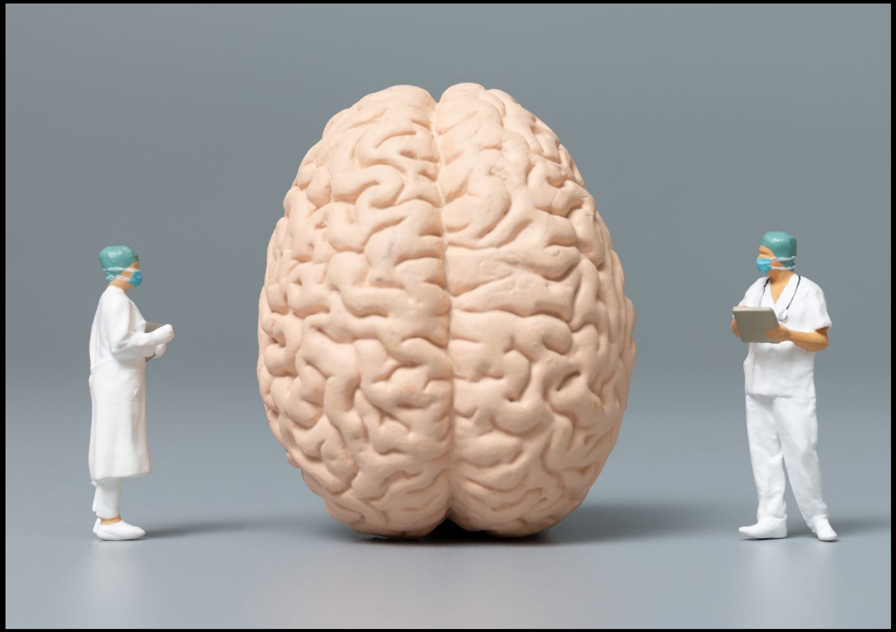



You
Tube

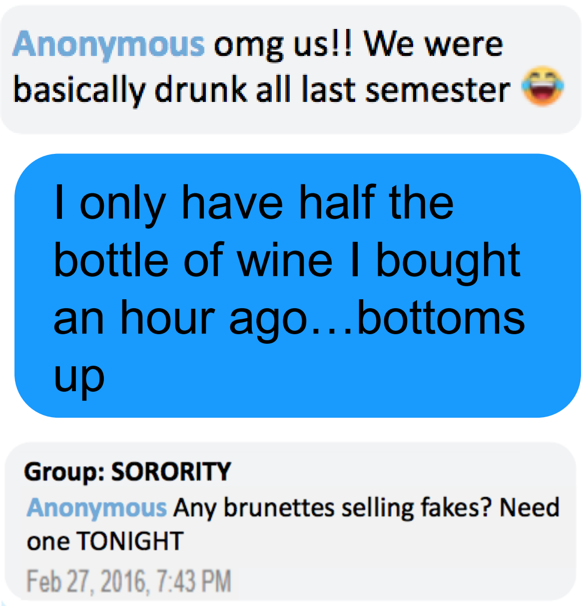
Personal Sensing and Mental Health

- Screening

- Symptom Monitoring



Feature Extraction



LIWC

Linguistic Inventory and Word Count

93 categories

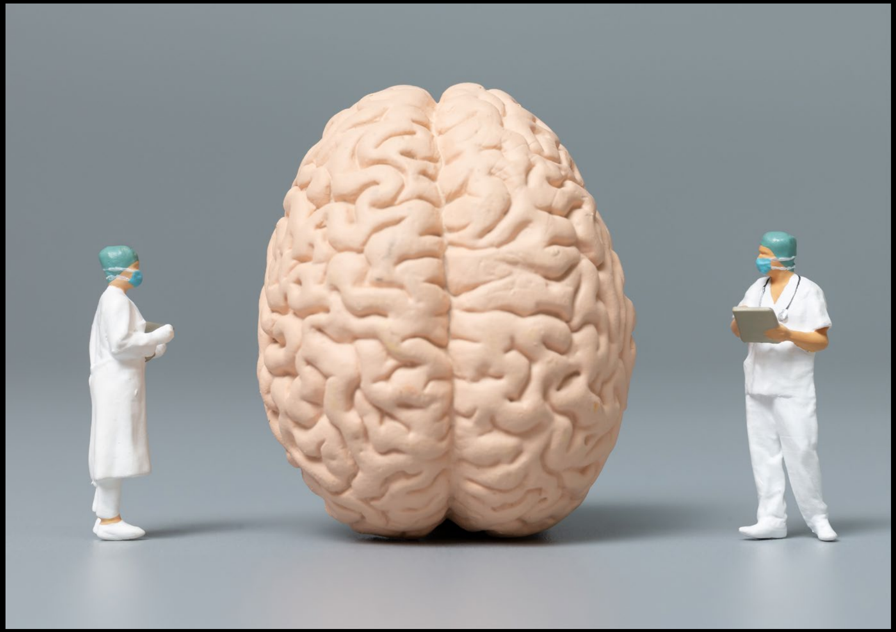
Anger	Sad	Social
0.00	0.00	7.09
0.36	2.40	16.59
.79	1.19	16.21

Wyant, Sant'Ana, & Curtin (Presentation at eLUCID8, 2019)

Personal Sensing and Mental Health

- Screening
  - Passive
  - Scalable

- Symptom Monitoring

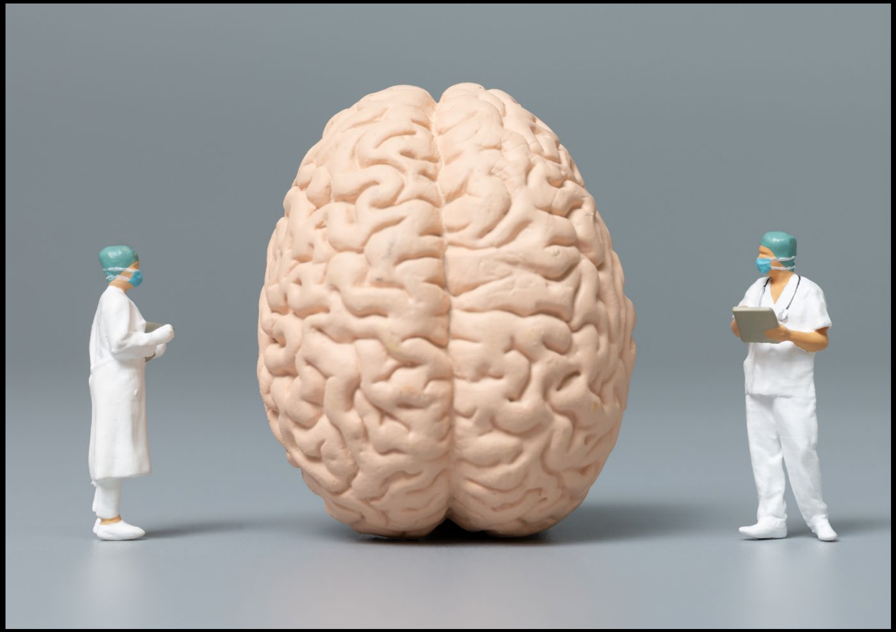


Bai et al., 2021 Barnett et al., 2018 Grünerbl et al., 2015

Personal Sensing and Mental Health

- Screening
  - Passive
  - Scalable

- Symptom Monitoring
  - Intervention prior to relapse



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Alcohol Use Disorder (AUD)

- AUD is a chronic relapsing disease
- Lapses are often early signs of relapse
- Detecting lapses before they occur may be an important step in treating AUD

Rounsaville, 2010 Witkiewitz, 2008 Jin et al., 1998

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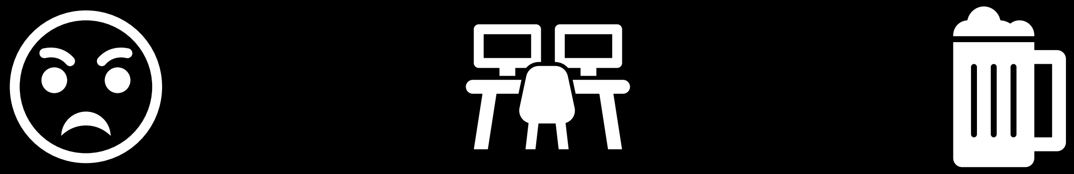
Rounsaville, 2010 Witkiewitz, 2008 Jin et al., 1998

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

Lapses

- Lapses are often preceded by external and internal factors



- Risk factors may be detectable in different time windows

Witkiewitz & Marlatt, 2004

Lapses

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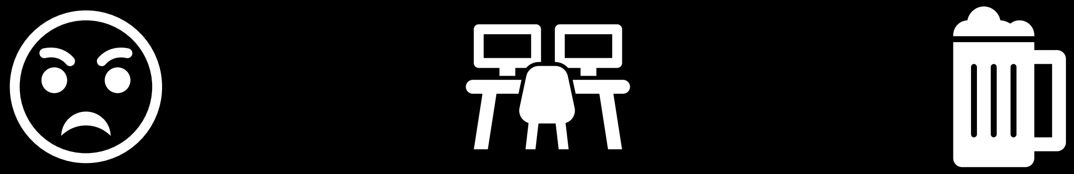

- Risk factors may be detectable in different time windows
- Current treatments may not detect early signs of lapse risk
- Personal sensing can capture fluctuations in lapse risk in real time

Witkiewitz & Marlatt, 2004

Prediction of stress and drug craving ninety minutes in the future with passively collected GPS data

David H. Epstein[1,✉], Matthew Tyburski[1], William J. Kowalczyk[1], Albert J. Burgess-Hull[1], Karran A. Phillips[1], Brenda L. Curtis[1] and Kenzie L. Preston[1]

Using machine learning to identify predictors of imminent drinking and create tailored messages for at-risk drinkers experiencing homelessness

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Cellular Communications

- Understudied personal sensing measure for AUD

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Longabaugh & O'Malley, 2010

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Longabaugh & O'Malley, 2010


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

Feasibility

- Low burden

Pew Research Center, 2021

Feasibility

- Low burden
- 97% of U.S. adults have a cellphone
- People generally find this to be an acceptable method

Pew Research Center, 2021

Acceptability of Personal Sensing among People with Alcohol Use Disorder

Wyant, Moshontz, Ward, & Curtin (in prep)

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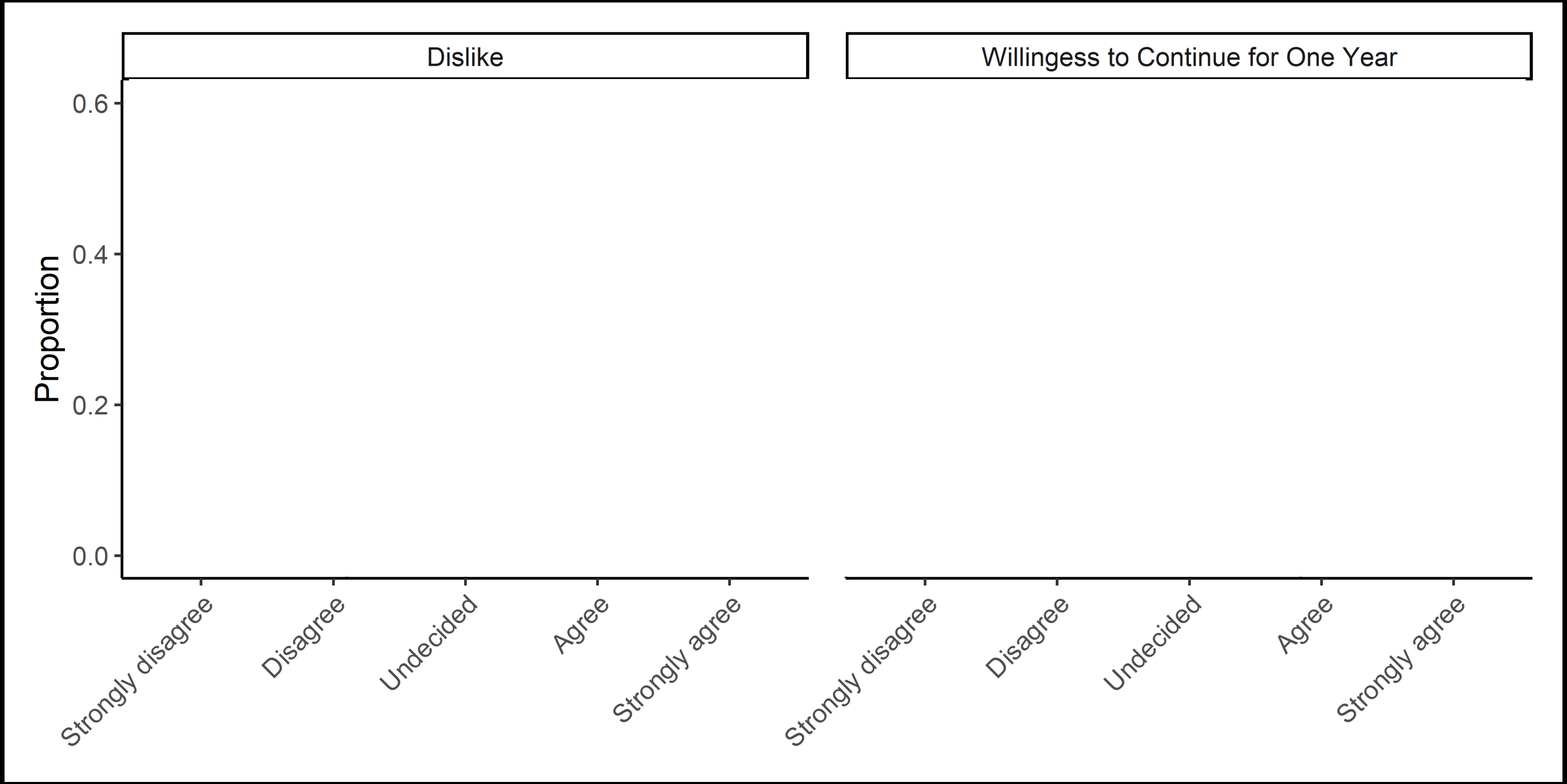

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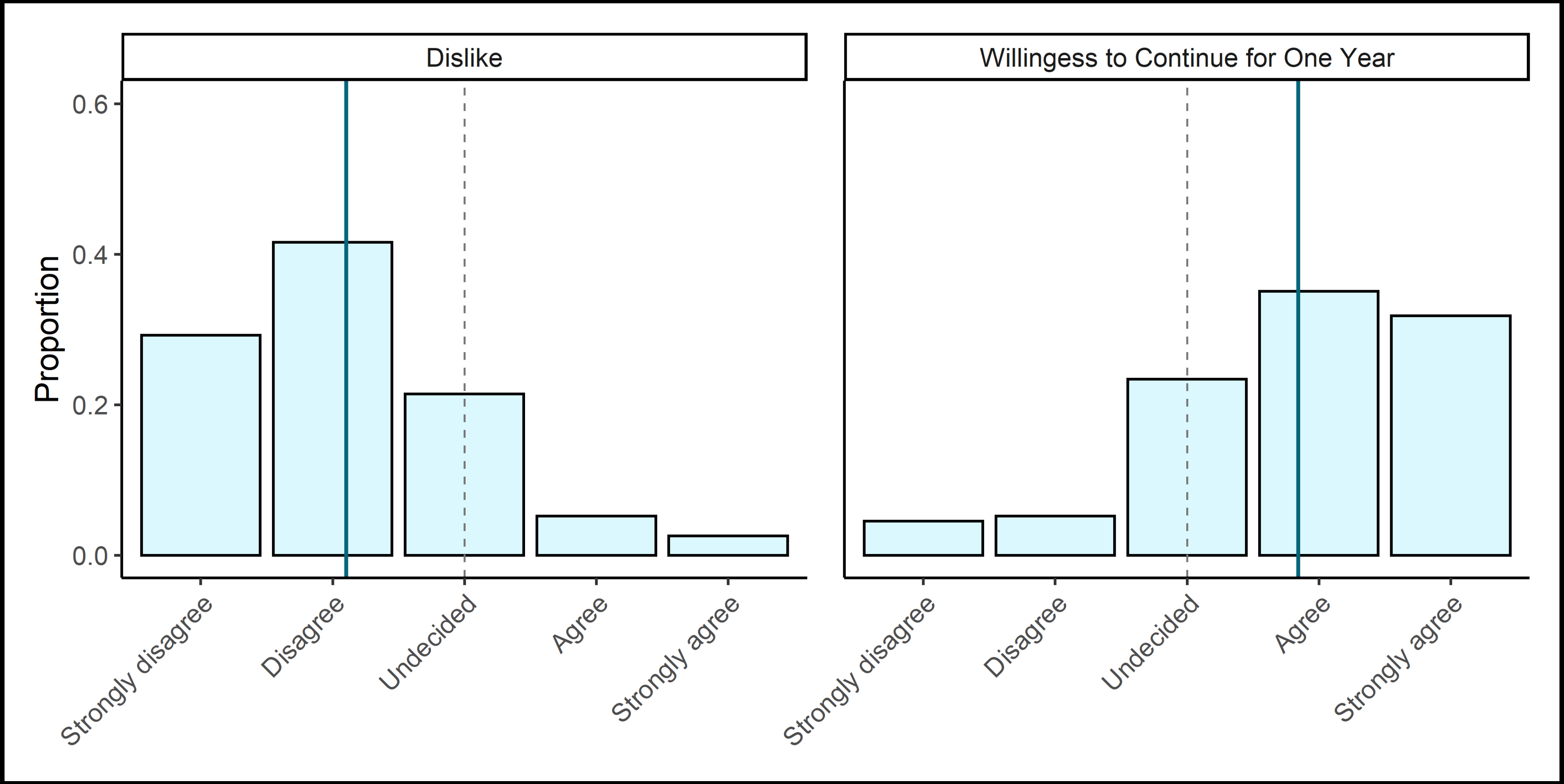
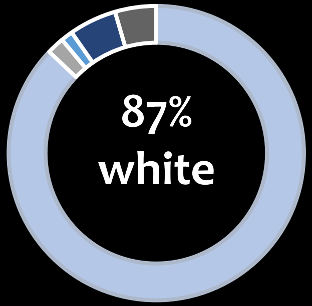
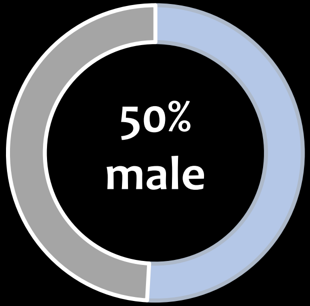


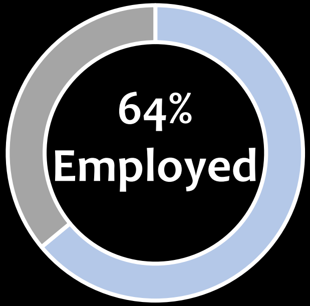
Wyant, Moshontz, Ward, & Curtin (in prep)

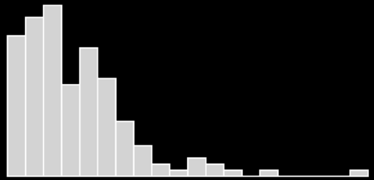
Can we predict alcohol lapses from contextualized cellular communication logs?

Participants (*N* = 154)

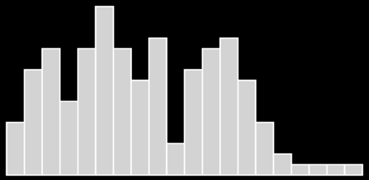




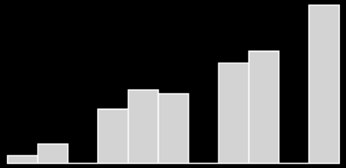




Income
***M* = 34,233**

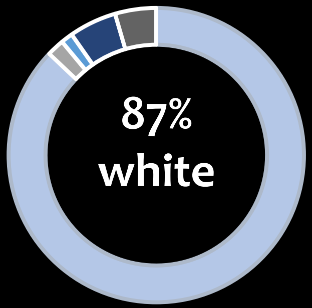


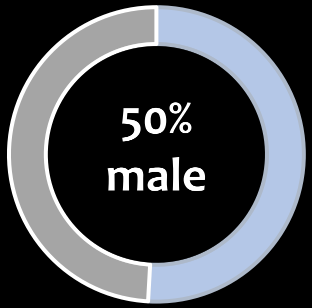
Age
***M* = 41**

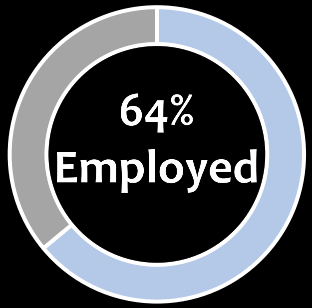


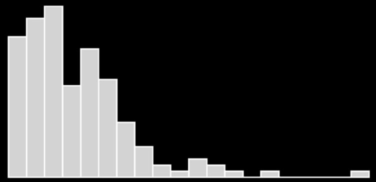
DSM5
9

Participants (N = 154)









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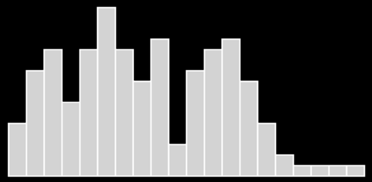

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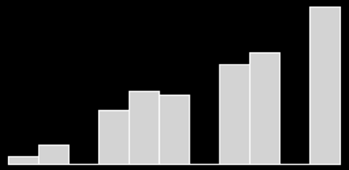

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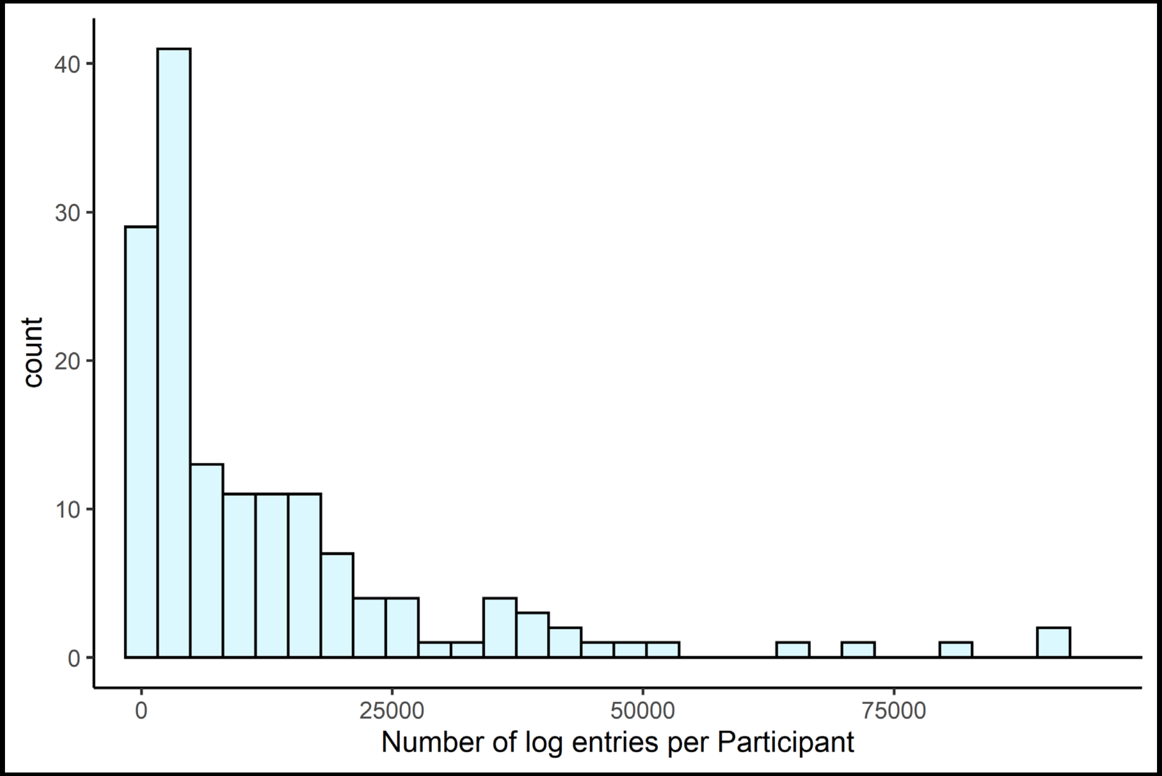
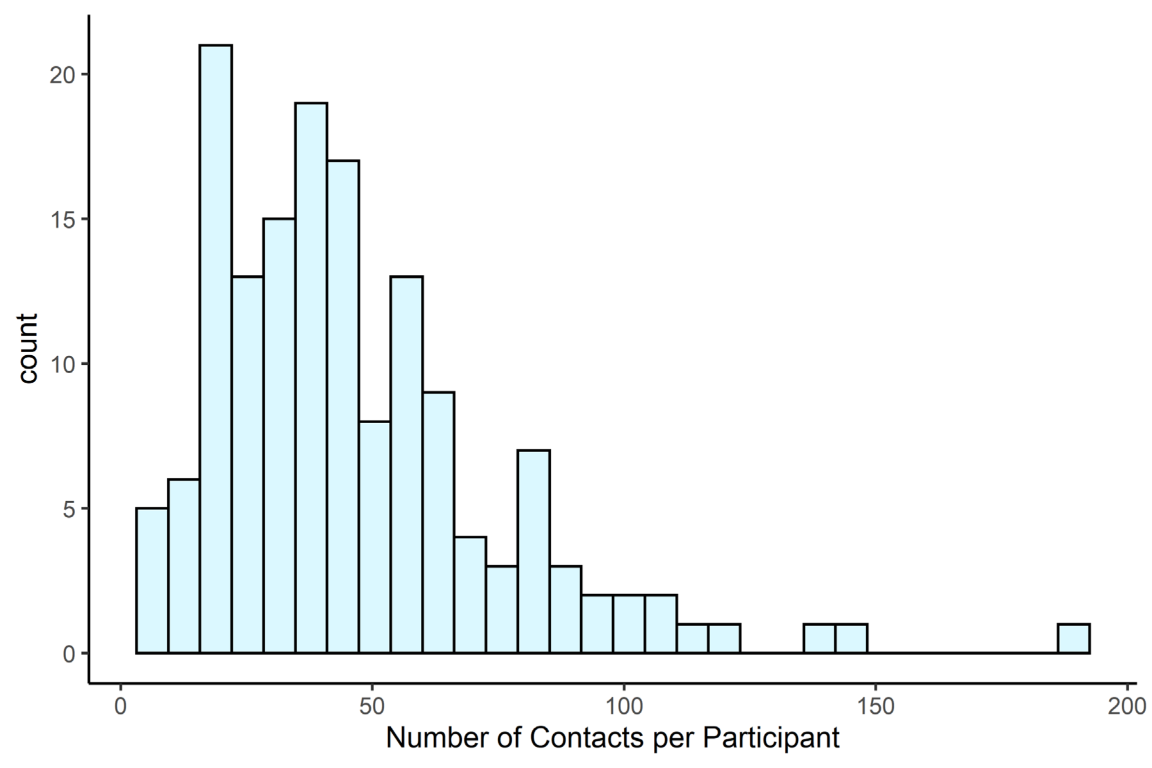
9

Communication Logs



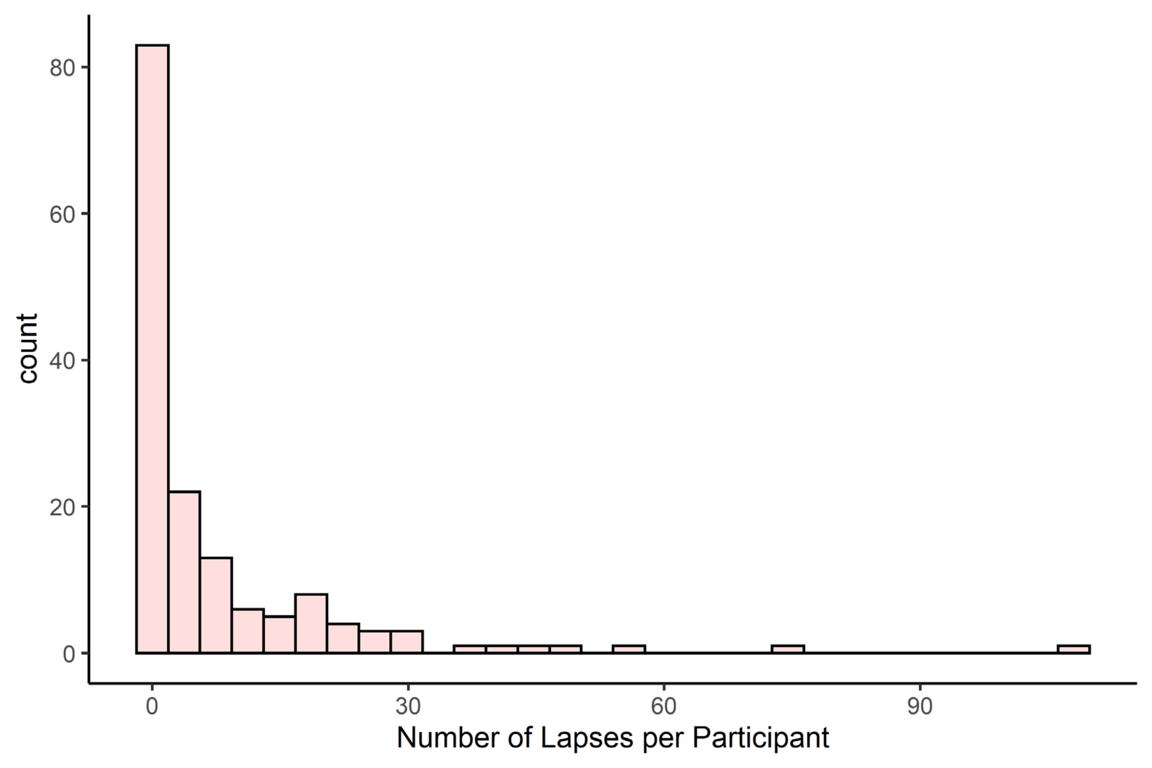
- 2676012 log entries
- 23 – 224062 logs per participant (M = 17377)

Contacts



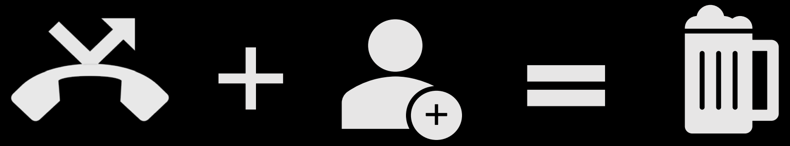
- 7211 contacts
- 5 – 188 contacts per participant (M = 47)
- We have context variables for over 70% of all log entries

Lapses



- 1,137 lapses
- 0 – 108 lapses per participant (M = 7.38)
- 86 participants reported a lapse

Modeling



- Feature engineering
- Prediction lead times
- Period durations for features
- Statistical algorithms
- Down sample non-lapses

Results coming soon…

Thank You!

Questions?

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