

# Using Cellular Communication Sensing to Support Early Recovery from Alcohol Use Disorder

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## Introduction

One of the biggest challenges in Alcohol Use Disorders (AUD) treatment stems from the chronic relapsing nature of this disease (Scott et al., 2005). People can relapse days, weeks, and even years after obtaining the goal of abstinence. At least 60% of AUD patients relapse to heavy drinking within 6 months following treatment (Kirshenbaum et al., 2009; Nguyen et al., 2020; Witkiewitz, 2011). At most 50% of people with an AUD achieve remission after several years (Fleury et al., 2016; Heyman, 2013).

Identifying initial lapses in early recovery is critical. Lapses – single episodes of alcohol use – are easy to define, have a clear onset, and are also clinically meaningful. They serve as an early warning sign of returning back to previous drinking behavior inconsistent with desired goals (Chung & Maisto, 2006; Marlatt & Donovan, 2005; **witkiewitzRelapsePreventionAlcohol2004b?**). Lapse predicts future lapses, with more frequent ones resulting in increased risks of relapse (Högström Brandt et al., 1999; **witkiewitzRelapsePreventionAlcohol2004b?**).

Current predictions of alcohol lapses rely heavily on self reports, which can be burdensome to measure in long run. Machine learning models leveraging ecological momentary assessment (EMA) measures have performed relatively well to predict goal-inconsistent alcohol use (Wyant et al., 2024). The surveys were collected up to four times daily for three months. However, constantly completing surveys makes it burdensome for AUD patients. Although most EMA relevant mental health research demonstrated modest compliance rates, their time windows last from two weeks to three months (Czyz et al., 2018; Hung et al., 2016; Mackesy-Amiti & Boodram, 2018; Porras-Segovia et al., 2020; **vangenugtenExperiencedBurdenAdherence2020a?**). The study length is insufficient because AUD is a chronic disease that requires

constant risk monitoring. As extended period of time is anticipated, users' perceived burden of answering surveys is presumably larger (Mogk et al., 2023). Although minimizing the number of items in the surveys and the frequency of prompting users to complete the surveys might help mitigate the associated burden, it can inevitably reduce the prediction precision and temporal precision of predictions.

Passive cellular communication sensing represents new opportunities due to its feasibility, relatively low burden on individuals and continuous data collection. In a smartphone-based sensing platform the primary expense on the individual is the smartphone. Smartphone usage is already widespread. Eighty-five percent of US adults have a smartphone and this number is consistent across all sociodemographic groups, including those in recovery programs for substance use (Center, 2021; Masson et al., 2019). Studies collecting passive data have demonstrated high acceptability from participants and higher compliance rates compared to active measures (Beukenhorst et al., 2022; Wyant et al., 2023). Further, risk monitoring using cellular sensing is temporally sensitive to fluctuating risks. Analyzing communication patterns can detect potential triggers in time without actively prompting users to reflect on their feelings at the moment or report their environment.

Cellular communications, with minimal contextual information, is embedded with potentially rich information that align with relapse antecedents. For example, social interactions can have important influences on drinking behavior (Alvarez et al., 2021; Hunter-Reel et al., 2009). We may be able to capture immediate risk based on who someone is calling or what time of day it is. Decreased interactions may signify isolation common with depressive symptoms, reaching out to people in one's social network could signify a positive coping strategy, or changes in patterns between a single person in one's social network could indicate conflict (Chih et al., 2014; Hufford et al., 2003; Miller et al., 2001).

This study aims at building machine learning models from cellular communications that identify *who* are at heightened risk for alcohol lapses, *when* they will lapse, and *why* they are at increased risk.

## Methods

### Transparency and Openness

We adhere to research transparency principles that are crucial for robust and replicable science. We reported how we determined the sample size, all data exclusions, all manipulations, and all study measures. We provide a transparency report in the supplement (Aczel et al., 2019). Our data, questionnaires, and other study materials are publicly available on our OSF page (<https://osf.io/wgpz9/>). Our annotated analysis scripts and results are publicly available on our study website ([https://jjcurtin.github.io/study\\_messages/](https://jjcurtin.github.io/study_messages/)).

## Participants

We recruited 192 participants in early recovery from AUD in Madison, Wisconsin, USA via print and targeted digital advertisements and partnerships with treatment centers. This sample size was determined based on traditional power analysis methods for logistic regression (Hsieh, 1989). We required that participants:

1. were age 18 or older,
2. could write and read in English,
3. had at least moderate AUD ( $\geq 4$  self-reported DSM-5 symptoms),
4. were abstinent from alcohol for 1-8 weeks, and
5. were willing to use a single smartphone (personal or study provided) while on study.
6. were not exhibiting severe symptoms of psychosis or paranoia.<sup>1</sup>

One hundred sixty-nine participants were eligible and enrolled in the study. Fifteen participants discontinued before the first monthly follow-up visit. We excluded data from one participant who did not maintain a goal of abstinence during their participation. We also excluded data from two participants due to evidence of careless responding and unusually low compliance. Our final sample consisted of 151 participants.

## Procedure

All procedures were approved by the University of Wisconsin-Madison Institutional Review Board (Study #2015-0780). Participants completed 5 study visits over approximately 3 months. Participants attended an in-person screening visit where we determined eligibility, obtained informed consent, and administered a battery of self-report measures. Eligible, consented participants returned approximately 1 week later for an intake visit. Three additional follow-up visits occurred about every 30 days that participants remained on study. At each follow-up visit, we downloaded participants' voice call and SMS text message logs from their smartphone devices, collected contextual self-report information about important contacts, and administered additional self-report measures.

Participants were expected to complete 4 brief (7-10 questions) daily ecological momentary assessments (EMA) for the duration of their enrollment. The first item on each EMA asked participants to report dates and times of any recent alcohol use. At follow-up visits, we verified lapse reports and queried participants about additional unreported lapses using a timeline followback measure. Additional sensing data streams (geolocation, sleep quality, and audio check-ins) were collected as part of the parent grant's aims (R01 AA024391).

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<sup>1</sup>Defined as scores  $>2.2$  or  $2.8$ , respectively, on the psychosis or paranoia scales of the Symptom Checklist-90 (Derogatis, L.R., 2000)

## **Measures**

### **Cellular Communication Logs**

#### **Context**

Participants were asked contextual questions about important contacts (people whom the participant communicated with at least twice by voice call or SMS text message in a one month period).



## Data Analysis Plan

## Model Configurations

## Feature Engineering

## Model Evaluation

## Model Comparison

## Feature Importance

## Results

### Participants

### Model Evaluation

### Model Comparison

### Feature Importance

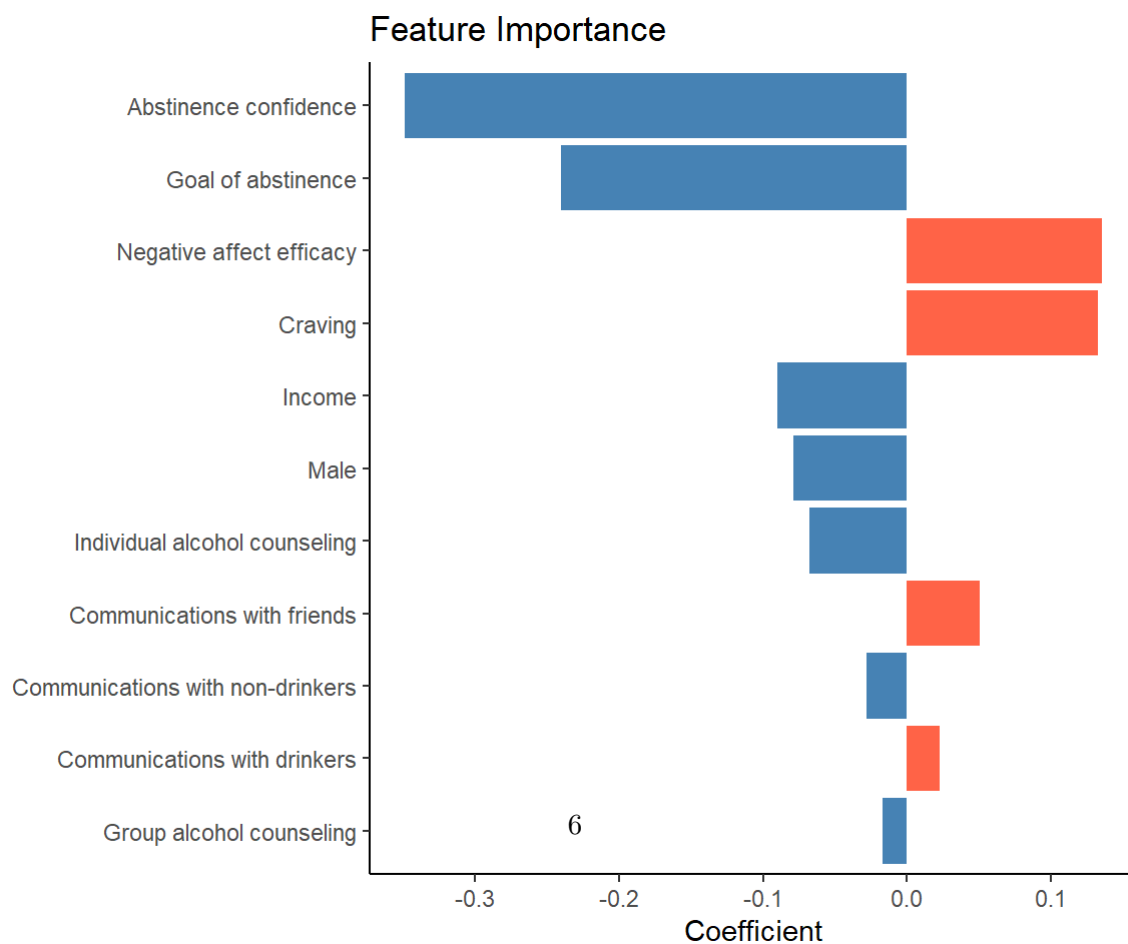


Figure 1: Global feature importance (glmnet coefficient) for the full model. Features are ordered by absolute coefficient value. Rate counts of communications with friends, non-drinkers, and drinkers were calculated across varying scoring epochs. Standard-

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## Discussion

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