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; Witkiewitz & Marlatt, 2004). Lapse predicts future lapses, with more frequent ones resulting in increased risks of relapse (Högström Brandt et al., 1999; Witkiewitz & Marlatt, 2004).

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; van Genugten et al., 2020). 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

Overview

This study analyzed data collected from 2017-2019 from a larger grant funded by National Institute of Alcohol Abuse and Alcoholism (R01 AA024391). In this paper, we focus on methods and measures that are relevant to this study. Additional details on broader methods and the full set of measures collected are described elsewhere (see https://osf.io/w5h9y/ and (Wyant et al., 2023; Wyant et al., 2024)).

Participants

Individuals in early recovery from AUD were recruited from Madison and surrounding area via social media platforms (e.g., Facebook), referrals from clinics, and television and radio advertisements. After initial phone screen, interested individuals came in-person to complete a more in-depth screening to determine their eligibility. We documented their demographic information. Inclusion criteria include that participants: 1) must be at least aged 18 or older; 2) must meet criteria for AUD with at least moderate severity (>four DSM-5 criteria); 3) must be abstinent from alcohol for at least one week and fewer than two months at time of intake; 4) must be able to read and write in English; 5) must be willing to use smartphone and their smartphone is compatible with our study technology. Participants were excluded if they have a lifetime history of severe and persistent mental illness. One hundred sixty-nine participants were eligible and enrolled in the study. After excluding participants who discontinued before the first follow-up session and those with low compliance rates and too few communications (<100 messages), we have a final sample size of 150 participants.

Procedures

The study lasted up to three months with five in-person visits. Participants completed an in-person screening visit to determine their eligibility, obtain their informed consent, and collect their demographic information and self-report measures. They then completed an intake session one week later and three follow-up visits afterwards spaced at one-month intervals. During each of the follow-up visits, a research assistant downloaded participants' SMS messages from their phone, verified reports of lapses and queried participants about any additional unreported laspes. Additional self-reported measures were obtained (see https://osf.io/w5h9y/).

Throughout the course of the study, participants were expected to complete four daily EMAs that asked about their alcohol cravings, risky situations, stressful/pleasant events, etc (Wyant et al., 2024). Notably, in the first item in the EMA survey, participants also reported their past alcohol use. Answer to this item will be used as the predicted outcome.

Results

Full Model

Baseline Model

Model Comparison

Feature Importance

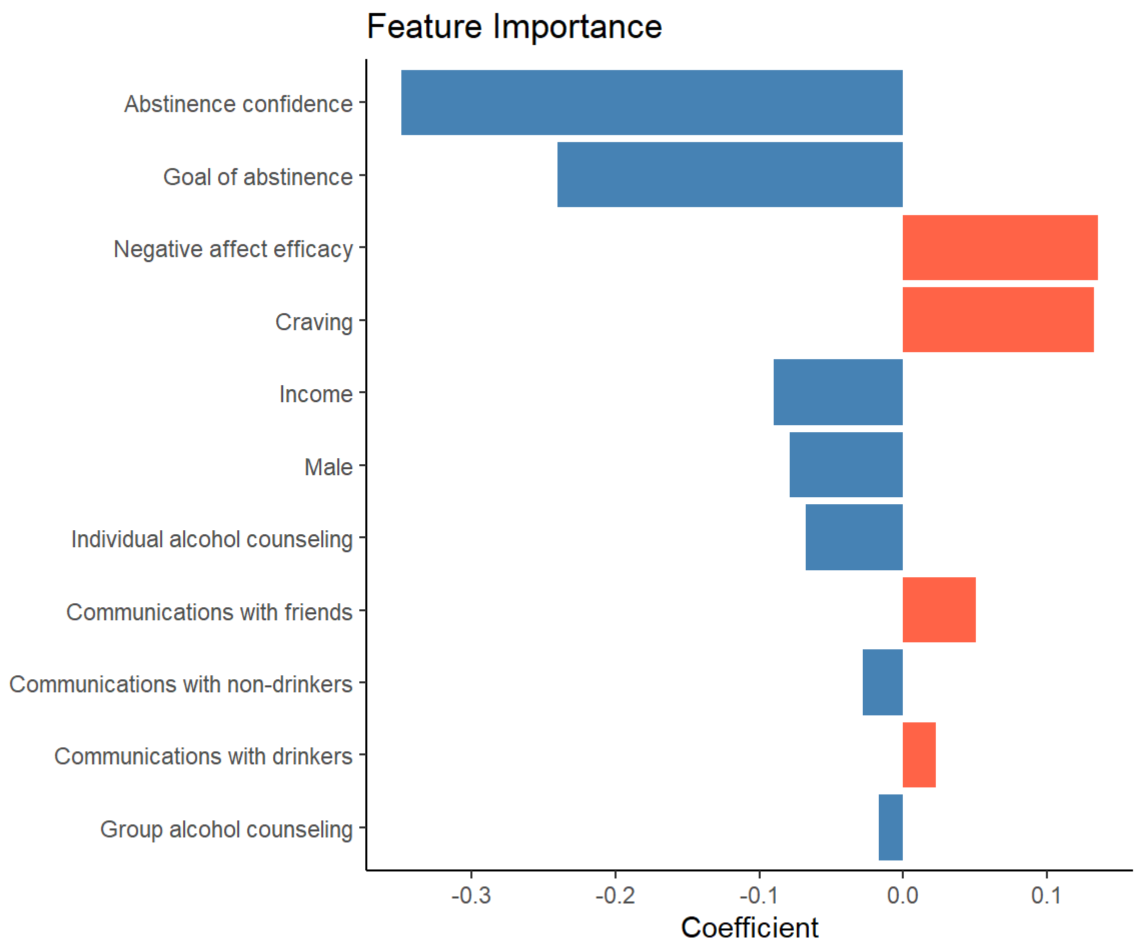

Figure 1: Global feature importance (glmnet coefficient) for the full model. Features are ordered by absolute coefficient value. Rate counts of communications with friends, non-drinkers, and drinkers were calculated across varying scoring epochs. Standardized coefficients were averaged across retained epochs to produce single aggregate feature importance score. Blue bars indicate higher feature values on average lower lapse risk. Red bars indicate higher feature values on average increase risk.

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Discussion

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