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Mobile phone sensors and supervised machine learning to identify alcohol use events in young adults: Implications for just-in-time adaptive interventions

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HIGHLIGHTS

- Mobile phone sensor data is useful in building accurate models to detect periods of drinking.
- Useful sensor features relate to activity/movement, phone use/calls, and keystrokes.
- Interventions could use phone sensor features to trigger remote support when it is most needed.

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ABSTRACT

Background: Real-time detection of drinking could improve timely delivery of interventions aimed at reducing alcohol consumption and alcohol-related injury, but existing detection methods are burdensome or impractical.
Objective: To evaluate whether phone sensor data and machine learning models are useful to detect alcohol use events, and to discuss implications of these results for just-in-time mobile interventions.
Methods: 38 non-treatment seeking young adult heavy drinkers downloaded AWARE app (which continuously collected mobile phone sensor data), and reported alcohol consumption (number of drinks, start/end time of prior day's drinking) for 28 days. We tested various machine learning models using the 20 most informative sensor features to classify time periods as non-drinking, low-risk (1 to 3/4 drinks per occasion for women/men), and high-risk drinking (> 4/5 drinks per occasion for women/men).
Results: Among 30 participants in the analyses, 207 non-drinking, 41 low-risk, and 45 high-risk drinking episodes were reported. A Random Forest model using 30-min windows with 1 day of historical data performed best for detecting high-risk drinking, correctly classifying high-risk drinking windows 90.9% of the time. The most informative sensor features were related to time (i.e., day of week, time of day), movement (e.g., change in activities), device usage (e.g., screen duration), and communication (e.g., call duration, typing speed).
Conclusions: Preliminary evidence suggests that sensor data captured from mobile phones of young adults is useful in building accurate models to detect periods of high-risk drinking. Interventions using mobile phone sensor features could trigger delivery of a range of interventions to potentially improve effectiveness.

1. Introduction

Binge drinking, defined as consuming > 4/5 drinks (women/men) per occasion, is a serious but preventable public health problem, with young adults disproportionately affected (Center for Behavioral Health Statistics and Quality, 2016). Digital interventions are a promising strategy to reduce excessive alcohol consumption, with most evidence for effectiveness in young adults (Carey, Scott-Sheldon, Elliott, Garey, & Carey, 2012; Fowler, Holt, & Joshi, 2016). Still, effects of digital interventions are typically small (Berman, Gajecki, Sinadinovic, & Andersson, 2016; Suffoletto et al., 2015), suggesting that designs are not optimized.

To improve longitudinal engagement and effects of digital interventions, the right support material should be delivered to the right

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person at the right time (Nahum-Shani et al., 2016). Therefore, a digital intervention aimed at reducing binge drinking should deliver support “in the moment”, that is, in the context of a drinking episode to enhance motivation for setting and keeping drinking limits, and to reduce the likelihood of negative alcohol-related consequences (i.e., reinforce explicit intentions). To accomplish these goals, it is critical that a digital intervention be able to detect when the person is drinking.

Recent developments in sensor miniaturization provide the ability to collect multi-modal data continuously from mobile phones with minimal participant burden. Continuous smartphone sensing can capture time-stamped data elements that can be used to track a person's daily routine in line with a computer science-based “context aware” theoretical framework (Abowd et al., 1999). Phone sensor data has been shown to be useful in inferring other states such as mood (Mohr, Zhang, & Schueller, 2017). Still, it remains unknown whether phone sensors could be useful in detecting periods of drinking.

In previous work (Bae et al., 2017), we described the computer engineering methods involved in using phone sensors for detection of drinking periods. In this study, we expand upon this work by describing how sensor features differ between periods of high-risk (e.g., binge) drinking, low-risk drinking, and non-drinking. We hypothesized that phone sensor features related to time (Del Boca, Darkes, Greenbaum, & Goldman, 2004), movement patterns (Freisthler, Lipperman-Kreda, Bersamin, & Gruenewald, 2014; Gruenewald, Remer, & LaScala, 2014), communication (Cavazos-Rehg, Krauss, Sowles, & Bierut, 2015; Moewaka Barnes et al., 2016), and psychomotor impairment (Scholey, Benson, Neale, Owen, & Tiplady, 2012; Suffoletto, Gharani, Chung, & Karimi, 2017; Suffoletto, Goyal, Puyana, & Chung, 2017) would contribute to detection models. We also examined the time it takes for machine learning models to reach stability in accuracy, and differences in model performance on weekends versus weekdays. We discuss implications of our findings for delivery of just-in-time mobile interventions.

2. Methods

This prospective study recruited a convenience sample of young adults with hazardous drinking to provide phone sensor and self-reported measures of alcohol consumption for 28 consecutive days. All participants provided informed consent and were offered resources for alcohol treatment. This study was approved by the Institutional Review Boards at the University of Pittsburgh and Carnegie Mellon University.

2.1. Participants

Recruitment occurred through an Emergency Department (ED) and college campus, using similar methods. From the ED, 51 medically stable patients who were not seeking treatment for substance use, not intoxicated, and who were going to be discharged to home were screened for eligibility. At the college campus, 17 students who responded to study flyers or a Craigslist posting were screened for eligibility. At both sites, individuals who were between the ages of 21–28 years of age, reported recent hazardous alcohol consumption based on Alcohol Use Disorder Identification Test for Consumption (AUDIT-C) score of ≥ 3 for women or ≥ 4 for men (Bradley et al., 2007) and at least one high risk drinking occasion ($>$ 4/5 drinks for women/men) on any day in the prior month were eligible for participation. We excluded those who did not own an iOS or Android phone. A total of 38 participants (21 ED patients, 17 students; see Table 1) met enrollment criteria and completed informed consent.

2.2. Procedures

Enrolled ED patients completed a brief questionnaire and downloaded the AWARE app (Ferreira, Kostakos, & Dey, 2015) to their phone in the ED. Enrolled college students presented to an on-campus office to complete the same questionnaire and download the AWARE app. All participants were instructed to keep the AWARE app open on their phone and to refrain from any non-drinking substance use (excluding cigarette use) during the study period. During enrollment, participants were provided with the definition of a standard drink (e.g., 12 oz. can of beer or 5 oz. glass of wine or 1.5 oz. 80-proof liquor) as well as an illustration of a typical standard drink for common beverage types: beer, wine, liquor. From the day after enrollment through 28 days, participants were sent a text-message (EMA) at 10 am: “Did you drink alcohol yesterday?” If they reported drinking, they received the following text queries: “Approximately what time did you start drinking?”, “Approximately what time did you stop drinking?”, and “How many standard drinks did you have during this period?” If there were multiple drinking episodes in a day, participants were instructed to report the episode when the largest number of drinks was consumed. All other potential drinking periods that day were coded as non-drinking. Participants received $20 for completing the baseline survey and $2 for each day they completed EMA.

Table 1
Sample characteristics.

Characteristics		ED patients (n = 21)	College students (n = 17)
Age, mean (SD)		23.1 (1.7)	23.9 (1.9)
Female sex, n (%)		7 (33.3)	8 (47.1)
Race	White	8 (38.1)	4 (23.5)
	Black	11 (52.3)	1 (5.9)
	Asian	1 (4.8)	12 (70.6)
	Other	1 (4.8)	0
Highest education	$<$ High school	2 (9.5)	0
	High school grad.	5 (23.8)	1 (5.9)
	Some college	11 (52.4)	3 (17.7)
	College grad.	3 (14.3)	13 (76.4)
AUDIT-C score		6.0 (2.2)	6.2 (3.4)
Other drug use, last month	Daily or almost daily tobacco	2 (9.5)	2 (11.8)
	Any cannabis	12 (57.2)	6 (35.2)

2.3. AWARE app

When downloaded, AWARE app (Ferreira et al., 2015), for iOS and Android, places an icon on the phone screen which, when opened, automatically begins recording sensor data without requiring further participant interaction. When AWARE is opened for the first time, a unique IDwas randomly generated for research purposes. AWARE temporarily stored the sensor data on a participant's device and then synchronized this information to a university server over a secure connection via Wi-Fi every 30 min, when available. We configured AWARE to collect 56 sensor features related to time (e.g., day of week, time of day), movement patterns (e.g., accelerometry, rotation), communication (e.g., phone calls, texts), and psychomotor impairment (e.g., keystroke speed; available for Android phones only).

2.4. Measures

2.4.1. Baseline questionnaire

Demographics. Participants reported age, sex, race, ethnicity, and education.

Drug use. NM-ASSIST (Humeniuk et al., 2008) assessed frequency of past month drug use (e.g., tobacco, cannabis, opiates).

Alcohol Consumption. AUDIT-C (Bradley et al., 2007), includes 3 items on drinking quantity and frequency in the past 3 months. AUDIT-C score $>$ 4 for men, and $>$ 3 for women is considered positive (Rubinsky, Dawson, Williams, Kivlahan, & Bradley, 2013).