Mobile sensing in substance use research - a scoping review.

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Abstract

Background

Addictive disorders and substance use are significant health challenges worldwide, and relapse is a core component of addictive disorders. The dynamics surrounding relapse and especially the immediate period before it occurs is only partly understood, much due to difficulties collecting reliable and sufficient data from this narrow period. Mobile sensing has been an important way to improve data quality and enhance predictive capabilities for symptom worsening within physical and mental healthcare but is less developed within substance use research.

Methodology

This scoping review aimed to reviewing the currently available research on mobile sensing of substance use and relapse in substance use disorders. The search was conducted in January 2019 using PubMed and Web of Science.

Results

Six articles were identified, all concerning subjects using alcohol. In the studies a range of mobile sensors and derived aggregated features were employed. Data collected through mobile sensing was predominantly used to make dichotomous inference on ongoing substance use or not and in some cases on the quantity of substance intake. Only one of the identified studies predicted later substance use. A range of statistical machine learning techniques was employed.

Conclusions

The research on mobile sensing in this field remains scarce. The issues requiring further attention include more research on clinical populations in naturalistic settings, use of a priori knowledge in statistical modeling, focus on prediction of substance use rather than purely identification and finally research on other substances than alcohol.

Introduction

Addictive disorders affect as many as 29.5 million people globally. Although there has been made substantial progress in our understanding of how addictive disorders develop and are maintained, they remain a public health challenge. Relapse is a core component of addictive disorders and the number of patients that relapse is high [1, 2]. International studies also show that only about 40-60 % of patients remain abstinent one year after treatment initiation [3].

An essential challenge in substance use research is thus to understand, predict, and identify relapse. In contrast to the knowledge about static or trait risk factors of relapse, the dynamics of the psychological and behavioral factors that are preceding and influencing the likelihood of imminent relapse, are less understood [1]. Lapses are often sudden and surprising to both patients and health care providers, complicating the reliable retrospective collection of data immediately preceding the lapse [4].

Up until recently, longitudinal and real-time data collection has typically been performed by prompting patients to complete questionnaires to assess dynamic states such as mood, cravings [5], cognitive functioning [6] and actual substance use on their portable device or by researcher follow-up [7]. This method of gathering information is commonly referred to as ecological momentary assessment (EMA). A challenge with studies demanding active participation from patients in data gathering is that they are perceived as burdensome by participants and hence generally suffer from poor compliance and data accuracy [8]. One review [7] found that compliance with EMA-procedures in substance use research varied greatly and generally fell below 70% across all designs for substance-dependent samples, below the generally accepted 80 % in social science research. Consequently, the validity and reliability of responses in real-time suffer, and the predictive value may be negatively influenced [9].

To overcome these issues of attrition and low compliance, researchers and clinicians have recently been considering the use of real-time data collection from different mobile sensors, like the ones available in smartphones, and to study how they relate to relapse [10]. Some studies even propose the approach of pure passive data gathering from mobile sensors, also called mobile sensing. This is already being used for research purposes in other mental health domains.

The question of making inference based on mobile sensor data is essential to make this field clinically meaningful. A range of studies has used directly measurable biological entities to create intuitive and direct inferences about alcohol and drug consumption, such as the alcohol metabolite Ethyl glucuronide (EtG) in sweat, measured by a wearable sensor on the skin of the subject [11]. Other wearable biosensors, such as electrodermal sensors measuring the amount of perspiration, skin temperature [12] and heart rate [13] gives indirect physiological data that may correlate with the intake of alcohol and drugs. Making inference from indirect behavioral data is often referred to as digital phenotyping. Appropriately analyzed data from the passive mobile sensing of behavior may inform clinical decisions for this clinical population [14].

Methodology

Research questions

This review aims to summarize the current state of published research on passive mobile sensing in substance use research by answering the following questions. What tools, sensors and analytical approaches are typically used? Which populations have been studied? And finally, what inferences are drawn based on mobile sensor data.

Literature review

Scoping review was chosen as methodology. There is still some variability in the execution of these reviews, however their advantage is that they are good at mapping research within an emerging topic or field to and contribute to the definition of its boundaries and concepts. This may be especially useful in cases where the body of literature has not yet been comprehensively reviewed and the research to some extent lacks uniformity both in concepts, analyses, type and amount of data [15]. So that it does not easily lend itself to systematic reviews [16]. In this case, it is still early in this research area, while at the same time there is a rapid technology development within smartphone technologies that may be best summed up with this methodology.

Procedure

Search terms

Substance use, substance abuse, addictive behavior, AND ambulatory assessment OR mobile sensing OR smartphone sensors OR mobile sensors.

Search procedure

The search was done using Web of Science and PubMed during the first 2 weeks of January 2019 as well as cross-referencing and reference section review in the final included publications.

Inclusion/exclusion of studies

Articles were included that measured behavioral features in the interaction with and transportation of mobile phones. Articles were excluded if they were merely technology focused, without any applied purpose. Studies requiring the subjects to enter data themselves actively were only included if they had a passive mobile sensing component. Studies using only physiological measurements such as heart rate, skin conductance etc. were also excluded, since these requires extra strain and equipment in many cases and thus not tap into behavior as such. Studies related to nicotine and tobacco were not included.

Only published, peer-reviewed publications were included. Sources such as dissertations and reports were excluded. Due to the rapidly evolving pace of mobile technology and analytical capabilities, the search included papers from 2015 and onwards, including also research in press up until the second half of January 2019.

Analysis and synthesis approach

For this review, articles were organized according to the type of method that was used for mobile sensing, the selected articles were read in full version and then entered into a table format to give an overview of authors, populations and methods of each study.

Results

In total, 329 studies were identified, of which 321 were excluded either based on exclusion criterias or as duplicates, then 2 studies were excluded as review articles, leaving 6 studies for review.

Table 1 Overview of included studies, BAL: Blood Alcohol Level, AUDIT: Alcohol Use Disorder Identification Test

Substances and populations investigated

The six included articles all studied subjects with high-risk alcohol consumption, none included clinical populations or populations using other substances than alcohol. The age groups studied were primarily young adults. The studies did not seem to have any obvious gender bias to the extent that gender was reported.

Bae, Chung, Ferreira, Dey, Suffoletto [10] included 38 non-treatment seeking young adults with a heavy drinking pattern, determined by AUDIT-C. The subjects were recruited through a hospital emergency department as well as a college student sample. The groups did not differ significantly in their AUDIT-C scores. In a another study, Bae, Ferreira, Suffoletto, Puyana, Kurtz, Chung, Dey [17] included 30 young adults with past hazardous drinking patterns as defined by the National Institute of Alcohol abuse and Alcoholism. The patients were recruited from an Emergency Department sample, Craigslist, existing participants pool and through flyers. Only patients not actively seeking treatment for substance use disorder were screened for inclusion. All potential subjects were screened using the AUDIT-C. A total of 38 subjects were recruited, 50 % female, and enrolled for the 28-day study.

Mariakakis [18] enrolled 14 young adults for their 1 week long study, the inclusion procedure is however not clearly described, except a statement that more participants were eager to join, but not able due to the burden of the study time, alcohol and pregnany testing.

In two studies using the same sample, [19, 20] the authors set out to determine Blood Alcohol Level (BAL) based on the gait features of users. The sample consisted of 10 young adults with a heavy drinking pattern, determined by AUDIT-C, that were seen in an urban hospital Emergency department. The subjects were required to have a drinking pattern characterized by drinking primarily on weekends. Subjects reporting conditions significantly impairment of memory or gait were excluded.

Arnold, LaRose, Agu [21] included six young adults with an AUDIT score equal or above 8 recruited by an e-mail list to faculty and students and their friends and families.

Technologies and techniques used

Bae, Chung, Ferreira, Dey, Suffoletto [10] assessed alcohol intake using EMA in the form of a daily question, if the participant confirmed intake of alcohol, they got three follow up questions to assess when they started and stopped drinking and how many standard units they drank. The study used the AWARE mobile sensing app framework and employed a total of 56 sensor features related to time, movement patterns, communication, and psychomotor impairment. Bae, Ferreira, Suffoletto, Puyana, Kurtz, Chung, Dey [17] also used the AWARE app and collected data from 14 different sensors using a total of 56 features. Also, the subjects were prompted to answer whether they consumed alcohol on the day before and the timing of this.

In Mariakakis, Parsi, Patel, Wobbrock [18] the subjects took part in a 1-week experimental study where alcohol was administered to the participants as to achieve a Blood Alcohol Level (BAL) of .08 measured with breathalyzers. Individuals with substance use disorders typically have issues with neurocognitive functioning [22, 23] and Mariakakis et al. (2018) developed and used the 'DUIapp' (Drunk User Interfaces) where the participants were required to perform a range of tasks that mimicked the ordinary use of an android phone and that tapped into psychomotor and cognitive functions. The study aimed to see if machine learning techniques would be able to predict BAL using the performance metrics on these tasks. The tasks included a swiping task, a balancing and heart rate task, a simple reaction task, and a choice reaction task. The tasks were then performed at different BAL after project administered alcohol and verification of BAL-level using a breathalyzer.

The subjects in Suffoletto, Gharani, Chung, Karimi [19] and Gharani, Suffoletto, Chung, Karimi [20] had the app 'DrinkTrac' downloaded to their smartphones. The app gives an EMA prompt for the cumulative number of drinks since the last report and a tandem psychomotor task, requiring the subjects to walk five steps in a straight line and rest while carrying their phone. The participants were prompted every hour between 8 p.m. and 12. A.m. to fill this out every Friday and Saturday for four consecutive weekends.

In Arnold, LaRose, Agu [21] the subjects installed a data gathering app on their smartphones ('AlcoGait') upon inclusion, that collected data relevant to the user's gait using the features gait cycle, stance phase, gait velocity, cadence, stride and step width of subjects. The study also gathered the subjects own estimate of alcohol consumption through EMA on the day after consumption.

Analytical approaches and results

In Bae, Chung, Ferreira, Dey, Suffoletto [10] the data was coded binary in the form of drinking or non-drinking, with only the indicated active drinking period being labelled as drinking. The authors created datasets with 30 min, 1 and 2-hour segments and coded the segments as non-drinking, low-risk drinking and high-risk drinking. Both Bayesian neural Networks, C4.5 decision tree and Random Forrest machine learning techniques were used on the test, of which Random Forrest performed best in predicting drinking. The study also looked at whether historical data preceding drinking onset improved model performance. In addition to temporal data (day of the week and time of day), the study was able to demonstrate that drinking was significantly correlated to specific sensor features and that adding historical data from 1-day prior to the drinking episode, improved model performance in predicting drinking. The authors concluded that machine learning models using input from mobile phone sensors achived an accuracy of 96 % compared to the 90% that was achieved with the time of day and day of the week as input alone.

Bae, Ferreira, Suffoletto, Puyana, Kurtz, Chung, Dey [17] used historical data from 1 h, 1, 2- and 3-day interval preceding the drinking episodes and used correlational analysis to determine which sensor features correlated well with the incidence of drinking. The authors used an information gain approach to determine which features were most important in understanding drinking incidence across intervals and chose the 20 most important features. Then they checked the performance of three machine learning classifier approaches (Random Forrest, C4.5 decision tree, and Bayesian network). Then the authors experimented with different time windows of data to be entered, ranging from 1 hour to 3 days. Finally, it was determined that 30-minute windows, with three days of historical data and 30-minute windows with one day of historical data, were superior for the detection of overall drinking and heavy drinking, respectively. The overall accuracy of random forrest model of predicting wither non-drinking, drinking or heavy drinking was 96,6%. When comparing [10] and [17] one should note that the first use 2 classes (drinking or not), and the latter uses three classes (no drinking/drinking/heavy drinking).

Mariakakis, Parsi, Patel, Wobbrock [18] used regression analysis with BAL as a label and estimated an exponential learning curve for the tasks across the five trials and compared it to a learning curve for sober subjects. The study went on to study whether individual tasks or different combinations of tasks and administration performed better or worse in determining BAL. The results were promising with this small dataset of only 67 sessions and they reached a mean absolute error of 0.005% +/- 0.007% comparing breathalyzer measurements of BAL with model estimated BAL.

Suffoletto, Gharani, Chung, Karimi [19] tested the feasibility of collecting gait-related features from mobile sensors during drinking episodes and drew inference about estimated blood alcohol levels (BAL) from sensor data as compared to measured BAL. To achieve this the authors employed a Bayesian regularized neural network (BRNN) to model the relationships between the recorded gait features and the estimated BAL. The main finding was that they were able to determine such a relationship and that subjects with elevated BAL over the legal limit would rarely be underestimated to have legal BAL. Gharani, Suffoletto, Chung, Karimi [20] went about the analysis in much the same way, still concluding that the BRNN was the most accurate method.

Arnold, LaRose, Agu [21] used a range of techniques to 'clean' extracted data from accelerometer sensors. As an example, data gathered by the accelerometer may express movement from walking, whereas hand-movements and repositioning of the phone may give irrelevant movement. The authors used a technique for frequency harmonization called 'Total Harmonic Distortion'. They also used different machine learning algorithms to try and determine the quantity of consumed alcohol (no inference about BAL). Comparing various machine learning techniques, they found that Random forest performed the best.

Discussion

This scoping review gave an overview of the current state of published research on passive mobile sensing of substance use. The goal was to summarize what tools and sensors are typically being used, secondly how the acquired data is being analyzed, thirdly how inference is drawn and finally what are the main knowledge gaps in this multidisciplinary field of research.

Inference was generally performed as a prediction task, with alcohol use as response. As noted, a range of neurocognitive phenomenons (such as impulsivity) have substantial theoretical and empirical predictive associations with relapse. Nevertheless, such mediating factors were not addressed by the identified papers.

The performance of the models were generally quite good. Most studies had small sample size and looked at making group-level models to identify the substance use episodes. Only one study [21] looked at making individual level identifications, which will probably be of most value for clinical work and the launch of just-in-time interventions in the future.

Studies on clinical populations and populations using other substances than alcohol were absent from this work. In other related clinical areas there has been done more work on clinical populations [24] [25]. Why the field of substance use research has had less progress using mobile sensing this far is open for speculation. The field is multidisciplinary ranging from clinical addiction science through data science and to software development. Thus, the data scientists and programmers might not yet have found addiction scientists with competencies and interests to advance the work in clinical populations and other substances. Also, the use of illicit substances is indeed illegal, maybe creating less of a willingness to participate and lower accessibility to the eligible subjects in this population, compared to somatic and psychiatric disorders.

The sensors used to extract relevant features for analysis in the identified studies are typically related to time, movement patterns, and psychomotor functioning. Relapse and alcohol consumption is empirically preceded by changes in neurocognitive functioning [23]. Some research in mobile sensing and assessment of cognition also exist [26], but we were not able to identify any research looking at sensing of fluctuations in the cognitive state, and its association to substance abuse. One might hypothesize that using variations in cognition as a mediating variable, might enable prediction of substance use.

Conclusion

The identified research is heterogenous in its use of sensors and features and outcomes, but homogenous when it comes to study populations. Research looking at other substances than alcohol remains scarce and there is a clear need for research on different substance using populations than alcohol. Studies in less controlled but more naturalistic populations may also be of great clinical value. Not only necessary for the identification and prediction of relapse, these methodologies also lends themselves to improving the understanding of relapse per se. Future work trying to predict imminent relapse might therefore benefit from integrating a priori models of relapse. The use of such information in models may enhance predictive validity and reduce 'noise' from irrelevant sensor data. Finally, as the performance of classification models and tools for the identification of ongoing substance and alcohol use are quite good, it might be an option to investigate models using mobile sensing of substance use predictions as dependant variables.

References

1. Brorson HH, Arnevik EA, Rand-Hendriksen K, Duckert FJCpr. Drop-out from addiction treatment: a systematic review of risk factors. *Clin Psychol Rev* **2013**;33:1010-1024.
2. Andersson HW, Wenaas M, Nordfjærn TJAb. Relapse after inpatient substance use treatment: A prospective cohort study among users of illicit substances. *Addict Behav* **2019**;90:222-228.
3. McLellan AT, Lewis DC, O'brien CP, Kleber HDJJ. Drug dependence, a chronic medical illness: implications for treatment, insurance, and outcomes evaluation. *JAMA* **2000**;284:1689-1695.
4. Chih M-Y, Patton T, McTavish FM, et al. Predictive modeling of addiction lapses in a mobile health application. *J Subst Abuse Treat* **2014**;46:29-35.
5. Fatseas M, Serre F, Swendsen J, Auriacombe M. Effects of anxiety and mood disorders on craving and substance use among patients with substance use disorder: An ecological momentary assessment study. *Drug Alcohol Depend* **2018**;187:242-248.
6. Schuster RM, Mermelstein RJ, Hedeker DJA. Ecological momentary assessment of working memory under conditions of simultaneous marijuana and tobacco use. *Addiction* **2016**;111:1466-1476.
7. Jones A, Remmerswaal D, Verveer I, et al. Compliance with ecological momentary assessment protocols in substance users: a meta-analysis. *Addiction* **2018**;114:609-619.
8. W. Adams Z, McClure EA, Gray KM, et al. Mobile devices for the remote acquisition of physiological and behavioral biomarkers in psychiatric clinical research. *J Psychiatr Res* **2017**;85:1-14.
9. Malhi GS, Hamilton A, Morris G, et al. The promise of digital mood tracking technologies: are we heading on the right track? *Evid Based Ment Health* **2017**;20:102-107.
10. Bae S, Chung T, Ferreira D, et al. Mobile phone sensors and supervised machine learning to identify alcohol use events in young adults: Implications for just-in-time adaptive interventions. *Addict Behav* **2018**;83:42-47.
11. Selvam AP, Muthukumar S, Kamakoti V, Prasad S. A wearable biochemical sensor for monitoring alcohol consumption lifestyle through Ethyl glucuronide (EtG) detection in human sweat. *Sci rep* **2016**;6:11.
12. Carreiro S, Chai PR, Carey J, et al. mHealth for the Detection and Intervention in Adolescent and Young Adult Substance Use Disorder. *Curr Addict Rep* **2018**;5:110-119.
13. Kennedy AP, Epstein DH, Jobes ML, et al. Continuous in-the-field measurement of heart rate: Correlates of drug use, craving, stress, and mood in polydrug users. *Drug Alcohol Depend* **2015**;151:159-166.
14. Onnela J-P, Rauch SL. Harnessing smartphone-based digital phenotyping to enhance behavioral and mental health. *Neuropsychopharmacology* **2016**;41:1691.
15. Peters MD, Godfrey CM, Khalil H, et al. Guidance for conducting systematic scoping reviews. *Int J Evid Based Healthc* **2015**;13:141-146.
16. Pham MT, Rajić A, Greig JD, et al. A scoping review of scoping reviews: advancing the approach and enhancing the consistency. *Res Synth Methods* **2014**;5:371-385.

17. Bae S, Ferreira D, Suffoletto B, et al. Detecting Drinking Episodes in Young Adults Using Smartphone-based Sensors: *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* **2017**.

18. Mariakakis A, Parsi S, Patel SN, Wobbrock JO. Drunk User Interfaces: Determining Blood Alcohol Level through Everyday Smartphone Tasks: *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems* **2018**:234.

19. Suffoletto B, Gharani P, Chung T, Karimi H. Using phone sensors and an artificial neural network to detect gait changes during drinking episodes in the natural environment. *Gait Posture* **2018**;60:116-121.

20. Gharani P, Suffoletto B, Chung T, Karimi H. An artificial neural network for movement pattern analysis to estimate blood alcohol content level. *Sensors* **2017**;17:2897.

21. Arnold Z, LaRose D, Agu E. Smartphone inference of alcohol consumption levels from gait: *2015 International Conference on Healthcare Informatics* **2015**:417-426.

22. Bouvard A, Dupuy M, Schweitzer P, et al. Feasibility and validity of mobile cognitive testing in patients with substance use disorders and healthy controls. *Am J Addict* **2018**;27:553-556.

23. Jones A, Tiplady B, Houben K, et al. Do daily fluctuations in inhibitory control predict alcohol consumption? An ecological momentary assessment study. *Psychopharmacology (Berl)* **2018**;235:1487-1496.

24. Jenkins C, Burkett N-S, Ovbiagele B, et al. Stroke patients and their attitudes toward mHealth monitoring to support blood pressure control and medication adherence. *Mhealth* **2016**;2.

25. Holtz BE, Murray KM, Hershey DD, et al. Developing a patient-centered mHealth app: a tool for adolescents with type 1 diabetes and their parents. *JMIR Mhealth Uhealth* **2017**;5.

26. Abdullah S, Murnane EL, Matthews M, et al. Cognitive rhythms: unobtrusive and continuous sensing of alertness using a mobile phone: *Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing* **2016**:178-189.