

Relapse prediction: A meteorology-inspired mobile model

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Abstract

Predicting relapses to binge drinking in non-dependent drinkers may now be possible with smartphones. Smartphones have been shown to help individuals reduce their drinking and may help binge drinkers accelerate that process. Predicting the weather has improved greatly over the past 50 years, but predicting a binge drinking episode may be less difficult. It is hypothesized that the number of factors with high predictive value for any particular individual may not be large. Collecting data over time, a smartphone should be able to learn which combination of factors has a high probability of leading to an episode of binge drinking.

Keywords

alcohol, binge drinking, idiographic, mobile, prediction, relapse

Several recent developments suggest that it may be possible to predict the probability of relapses to an episode of binge drinking and to help people avoid such incidents. Fifty years ago, accurately predicting the path of a hurricane was not possible (Roulstone and Norbury, 2013), but in 2012, most of the best US computer models accurately predicted hurricane Sandy's "behavior." With the arrival of predictive analytics and smartphone apps capable of collecting data on an individual's sleep, moods, behaviors, locations, and connections with people over time, the ability to develop software that will predict the probability of a relapse to binge drinking—like the probability of severe weather—may be at hand.

Various terms for binge drinking exist in the literature. A recent Federal study (Esser et al., 2014) of 138,000 people defined binge drinking as binge drinking, heavy drinking, any underage drinking by 18–20 year olds, or any drinking in the past 30 days by pregnant women. Binge drinking for men was defined as five or more drinks on a single occasion and for women four or more drinks on a single occasion. Heavy drinking for men was defined as 15 or more drinks per week (DPW) and for women eight or more per week. This article focuses on single-episode binge drinking and is restricted to binge drinking, as defined above.

The recent Federal survey (Esser et al., 2014) also concluded that 90 percent of the "excessive drinkers" and "binge drinkers" in this country are not alcoholics; they do not meet the *Diagnostic and Statistical Manual of Mental Disorders*, Fourth Edition (DSM-IV) criteria for dependence. A closer look at the Federal data also reveals that 43 percent in the 18–24 age group reported binge drinking and 40 percent in the 25–34 age group. But the number drops to 30 percent for the 35–44 age group and 22 percent for the 45–64 age group. That is, over a 40-year period, millions of people stop binge drinking as they age. However, millions also continue the behavior and, as the Federal data suggest, take years to change. Along the way, they may do considerable harm to people around them and are a significant cost to society (Bouchery et al., 2011, 2013; Naimi, 2011; Rehm et al., 2009). A study by Woerle et al. (2007) in New Mexico indicated that binge drinkers cost more to the

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state of New Mexico than the heavily dependent drinkers upon which the state spends much of its money.

Increasing research (e.g. Carballo et al., 2008; Dearing et al., 2013; Jackson et al., 2001; Klingemann et al., 2009; Littlefield et al., 2010; Lopez-Quintero et al., 2011; Witkiewitz et al., 2014) indicates that most people recover from addictive problems on their own over time as they mature and make changes in their lives. Research also indicates that binge drinkers generally do not think that they need treatment and/or do not seek treatment (Edlund et al., 2009; Grant, 1997; Klingemann et al., 2009). Saunders et al.'s (2006) study suggests non-treatment-seeking may be due more to person-related barriers, such as shame, than treatment-related barriers, such as cost. Corrigan (2004) noted the negative impact on treatment seeking of both self-stigma and public stigma. Another person-related barrier may be a desire to solve the problem on one's own without treatment (Cunningham et al., 1993). The ability to use smartphone apps privately in an attempt to change drinking behavior may make them especially appealing to binge drinkers.

Dynamic, metastable systems

The importance of both linear and non-linear dynamic models for understanding psychopathology, including alcohol use disorders (AUDs), has become increasingly clear in the last decade (Fisher, 2015; Piasecki et al., 2002; Warren et al., 2003; Witkiewitz, 2008, 2011; Witkiewitz et al., 2007, 2014; Witkiewitz and Marlatt, 2007). In the case of binge drinkers, the way they moderate their behavior may be quite different from the way alcohol-dependent drinkers cut down. For example, the findings of one study (Witkiewitz et al., 2014) suggest that non-treatment-seeking heavy drinkers—defined by the authors as “more than five drinks per occasion” (p. 415)—may manifest more linear forms of drinking-behavior change over long time periods (weeks and years) than heavy drinkers who have been in treatment.

The above research is based on group data. Recently, the development of various ecological momentary assessment (EMA) techniques offers an opportunity to create an idiographic and quantitative science of drinking behavior. Smartphones coupled with EMAs reveal significant individual differences in the dynamic manner in which thinking, feeling, and behaving interact over time (Beckjord and Shiffman, 2014; Freisthler et al., 2014; Heron and Smyth, 2010; Neal et al., 2006; Ramirez and Miranda, 2014; Shiffman, 2013; Wray et al., 2014). Fisher (2015), for example, found that in three of his subjects with generalized anxiety disorder, greater avoidance led to more worrying. But in one subject, the opposite was true; avoidance behavior led to less worrying.

On a moment-to-moment basis, binge drinkers may also behave like metastable systems. A metastable system

appears stable, but a small change in the system may subsequently lead to a very large change (Fingelkurts and Fingelkurts, 2004; Outlier and Kelso, 2006; Rabinovich et al., 2008); tornadoes (and avalanches) are good examples. In the case of binge drinkers, they may appear to be stable and doing well, but given specific conditions, their pattern of behavior may change radically. Like most people, they may perceive themselves as reasonably stable systems over time. In addition, the experience of multiple days of drinking without problems may convince them that the likelihood of a major disruption to the system is unlikely. However, they might better be thought of as metastable systems; a relatively small change in one or more factors may lead to a dramatic—and for the individual, perhaps surprising—change in behavior. To date, EMA studies have not investigated the hour-to-hour changes in drinking throughout an evening, but that non-binge drinking may unexpectedly turn into binge drinking is well known to binge drinkers and clinicians who work with them.

Positive feedback loops

Binge drinking and tornadoes may have another characteristic in common. Positive feedback loops may play a key role in both. Positive feedback loops increase the speed of change. The weather preceding a tornado may appear as only a combination of dark clouds and some wind. However, an updraft of warm air may begin to pull even more warm air up into the sky, eventually combining to form a swirling vortex completely out of character to anything preceding it. A similar process is hypothesized to function in binge drinking. Drinking leads to more drinking, which leads to even more drinking (cf. Dorrian, 2012). However, this is not always the case. Certain factors must combine to start a positive feedback loop.

In the clinical setting, Ellis (1962) was perhaps one of the first to argue for the importance of what he called the “secondary symptom,” that is, the tendency for clients to make matters worse by getting depressed about being depressed or panicking at the first sign of panic. A positive feedback loop of negative affect about negative affect may build over time and destabilize a person's behavior.

Marlatt and Gordon (1985) coined the term “Abstinence Violation Effect” for the positive feedback loop in which feelings of shame and lack of self-control following a relapse lead to more drinking and a temporary giving up of any attempt to control behavior. Muraven et al. (2005a), using an EMA longitudinal design with hand-held computers, found that social drinkers who attempted to limit their drinking drank more after they violated their limit. Collins (1993) labeled this the limit violation effect (LVE). Muraven et al. (2005b) also found that heavy drinkers were more distressed by violating their intended limit than light drinkers and, again, that distress led to more binge drinking in the future, not less, as might have been expected. In

effect, the negative affect produced by a failure of self-control appears to be a vicious circle, which Muraven et al. (2005a) hypothesize may explain why some heavy social drinkers turn into dependent drinkers.

Smartphones coupled with predictive analytics offer an opportunity to develop quantitative, idiographic approaches over long time periods to learn how various factors combine in a unique individual and heighten the probability for an episode of binge drinking. The conditions that have a high probability of creating tornados have now been identified (e.g. Bolton et al., 2003), and severe weather warnings are now common in many parts of the country. It is hypothesized that smartphones could provide similar warnings of the probability of an episode of binge drinking.

Mobile applications (apps)

Many people, especially young people, have enthusiastically embraced mobile technologies to help them better self-regulate various unique, everyday behaviors, such as eating, going to the gym, and money spent on drinks. Apps currently exist that purport to help a person monitor all types of behavior, for example, walking, heart rate, and number of drinks. Kuhn et al. (2014) reported that a mobile application for help with post-traumatic stress disorder (PTSD) was downloaded more than 130,000 times in 78 countries. In an evaluation of the program with 45 veterans, they found that the vets reported the program to be helpful with acute distress and with sleep.

Cohn et al. (2011) found 202 apps that “utilized some empirically-based principles of alcohol treatments” (p. 2211) such as motivational counseling or self-control training. Holland and Cherney (2015) reviewed 10 apps for “recovering alcoholics.” Some offered prayers and meditations; others offered the user the opportunity to track one’s drinking across a month’s time. Gonzalez and Dulin (2015) found that a smartphone intervention program resulted in a significant decrease in the percentage of nondrinking days, percentage of heavy drinking days and DPW. They also found that on the weeks that the program was used more often, users reported fewer heavy drinking days and fewer drinks per day. However, none of the apps attempted to predict a relapse to binge drinking.

Gustafson et al. (2014b), p. 324) reported on a randomized clinical trial of the Addiction Comprehensive Health Enhancement Support System (A-CHESS), which provides “monitoring, information, communication and support services to patients, including ways for patients and counselors to stay in contact” (p. 566). At both the 4- and 8-month follow-up, the A-CHESS group reported significantly fewer “binge drinking days” during the 30 days prior to the assessment.

A-CHESS was designed for patients who had been hospitalized and were diagnosed as alcohol-dependent. However, there is no reason that A-CHESS, if programmed for cutting

down, as opposed to abstinence, could not be used by binge drinkers. The A-CHESS smartphones included a “panic button,” which, when activated, connected patients to counselors or A-CHESS programs. They were also set up with a wide variety of helpful suggestions, for example, “healthy events of interest to the patient,” “poignant memories from previous use,” and “key triggers and interventions likely to help deal with those triggers” (Gustafson et al., 2014b), p. 329), which the patient inputted at the time he or she was given the smartphone with A-CHESS on it. Binge drinkers could do the same. A-CHESS also included software that permitted patients to text a request for help to pre-approved friends and family who might have been nearby. Binge drinkers could program the phone to connect them with another person, for example, a supportive significant other or a therapist or coach. In addition, a GPS Tracker included with A-CHESS passively activated the panic button if a patient got close to a location which had been identified as a trigger location in the past. Such an app, if readily available, with or without a connection to a professional counselor, would probably be very useful to and popular with binge drinkers who are trying to change their drinking behavior.

Active versus passive inputting of data

Currently, mobile apps that rely on the user actively entering data, for example, each drink during the evening, provide suggestions that have been shown to help people significantly cut down their drinking, for example, A-CHESS. Exactly which kinds of messages may be more motivating is currently under investigation (Muench et al., 2013). However, ideally, a predictive app will be more useful if, for the most part, it passively collects data. That is, it is not dependent on the user entering data and will still provide a prediction of the probability of binge drinking. Time of day, day of the week, and location can be factored in relatively easily. Lack of adequate sleep leading to fatigue is measurable passively, but, to date, how accurately that can be done is not clear. Moodscope (LiKamWa et al., 2013) is one of the first attempts to measure affect passively; whether negative or positive affect contributes to more accurate predictions may vary from individual to individual. No one to date has developed an app to passively measure blood alcohol levels, but passively tracked speech activity is being studied to measure mood swings in bipolar patients (e.g. Faurholt-Jepsen et al., 2014; Grunerbl et al., 2014). Changes in speech activity may also work for measuring the increasing severity of risk as the number of drinks consumed increases.

As discussed previously (Gustafson et al., 2014b)), the A-CHESS user’s phone GPS system passively alerts the owner of being near a location previously identified/inputted as a binge drinking environment. A-CHESS then offers practical suggestions for avoiding the location. These suggestions appear to be especially effective if they are tailored to the individual’s idiographic historical/longitudinal data.

It is not difficult to envision an app that would give something akin to a “severe weather warning” and the probability of a relapse to binge drinking. Like the weather alert, it could not only signal a probability of binge drinking but also include individually tailored suggestions for actions that could be taken, for example:

Severe Overdrinking Alert: Given the time of day, where you are and how tired you are, you have a 98% risk of overdrinking. Leaving the location is a good idea if you want to stick to your long-term goals.

Note to self: In the past, being in Joe’s bar has led to overdrinking 87% of the time.

... or, depending on the individual’s drinking pattern:

Note to self: Drinking alone at home has led to overdrinking 95% of the time. It led to overdrinking last Tuesday and the Saturday before that.

Severe Overdrinking Alert: Currently, the probability of overdrinking is 95%. You are unusually tired. You have slept 5 hours less than normal over the past 3 days. This means that you are much less able to self-regulate. Going home and getting some sleep is not as exciting an idea, but it is probably the right idea in terms of your long-term goals.

Note to self: It has been 32 days since your last overdrinking episode. This number of days has been a problem for you in the past. You are 93% more likely to overdrink today if you go to a bar.

“Overdrinking” is not a term currently used by researchers; however, idiographically, it may be more meaningful to users (similar to the term “overeating”) than “binge drinking,” considering that the individual is about to consume or has consumed more drinks than he or she had intended.

Relapse prediction

Research consistently suggests that individual human behavior may not be as unpredictable as it seems (Ramos et al., 2011; Song et al., 2010), and predicting the probability of an episode of binge drinking may not require the sophisticated models and computing power necessary for predicting storms. Every hurricane is quite distinct and only “behaves” once; for example, it moves up the east coast of the United States only once. The next hurricane will be like a completely different individual. In contrast, an individual often engages in quite similar behavior day after day. To predict an individual’s behavior, it is key to collect data on the individual over time.

In the past, most researchers looking for predictors of relapse focused on dependent drinkers, not binge drinkers. That research suggests (Epler et al., 2014; Kuerbis et al., 2014; Witkiewitz, 2011; Witkiewitz and Marlatt, 2004) that many factors may combine to contribute to a relapse, but

several seem much more significant than others. Some are internal factors, for example, self-efficacy, and some are external, for example, bars and fraternity houses. Some may change over time and have been described as “phasic,” for example, affective states and substance use; those that appear to be much more stable have been described as “tonic,” for example, family history and comorbidity (Witkiewitz and Marlatt, 2007). Looking at problem drinkers, Miller and Joyce (1979) found that both less dependence and less family history of drinking predicted better moderation outcomes. Witkiewitz (2008) found that greater alcohol dependence predicted heavier drinking and a lower probability of moderate drinking. Kuerbis et al. (2014) found that motivation and self-efficacy predicted better moderation drinking outcomes.

In the most ambitious and successful attempt to date to predict lapses, Chih et al. (2014) developed a smartphone app that accurately predicted, within a week, 21 of 28 patient lapses. (A “lapse” was defined as “an initial setback” by Witkiewitz and Marlatt (2004) and a “relapse” as “return to the previous problematic behavior (pattern)” (p. 224); for binge drinkers, “relapse” seems the more appropriate term.) Patients participated over an 8-month period and checked in once per week using A-CHESS. A variety of risk items and protective factors were combined, and then a Bayesian network model was used to develop the predictive model. Based on the information inputted, if a lapse was predicted, not only was an alert sent to the patient’s phone but also helpful, lapse-prevention information, for example, ways to prevent a lapse, were also sent. These included texts specifically tailored to the individual’s preferred ways of preventing a lapse, for example, going for a run or attending an Alcoholics Anonymous (AA) meeting, as well as the reasons that that person had previously given for wanting to stay sober. The program also successfully demonstrated that it could improve its predictive capability as time went on and more data on a patient were collected. The participants in the Chih et al.’s (2014) study had all been diagnosed as alcohol-dependent (DSM-IV); only 20 percent were employed; all had been in rehab; and 49 percent had mental health problems, as well. Data were also not collected passively on an ongoing basis, and, as noted by the authors, the lapses were self-reported.

In developing a relapse prediction system for binge drinkers, the collection of person-centered data over time via mobile phones will clarify which factors contribute most powerfully to a relapse. At this point in time and for this discussion, and based on clinical observation, it is hypothesized that as few as five factors may be adequate to predict a relapse in a particular binge drinker.

Time—hour of the day

Humans must manage both changes in the internal and external “weather,” and the two interact (Araújo et al., 2006). Human internal systems are dynamic and in a

continual state of change; humans do not have the same neurochemistry in the morning as they do in the evening (e.g. Shannon et al., 2013). Heart rates and insulin levels vary throughout the day (Kim et al., 2014; Saad et al., 2012). At the same time, the external environment is changing as well. The day is waning, lights are coming on in bars and restaurants, and friends are going out for a drink.

Time of the day has only recently been studied as a factor that may contribute to a relapse (Rainham et al., 2010; Shiffman, 2013). This may have been because there was little interest in specifically when a lapse or relapse occurred. More likely, prior to such methods like EMA, there was no effective way to assess accurately drinking over time.

Todd et al. (2009) found that among their sample of non-dependent participants (mean age, 43.5 years; median income, US\$60,000–US\$70,000; average education, 15.9 years), 97.3 percent had not started drinking at 11:30 a.m. They also found that participants started drinking significantly later in the day on weekdays compared to weekend days. Kuntsche and Labhart (2012), using EMA and smartphones, found that more drinking occurred in the evening and on Thursdays, Fridays, and Saturdays, although this may be partly due to the fact that their participants were college-age students.

Whatever models and programming apps are developed, they must take into account that many antecedents to a relapse become stronger through the day.

Time—day of the week

Just as time of the day may be one of a group of factors that, when taken together, lead to binge drinking, the day of the week (as noted above, Kuntsche and Labhart, 2012) may also add strong predictive value. For example, Demers et al. (2002), in a survey of over 26,000 drinking occasions among 6850 college drinkers, found that while only 6.6 percent of respondents reported drinking on Wednesday, 13.7 percent reported drinking on Thursday, and 28.4 and 37.9 percent on Friday and Saturday, respectively. In Wood et al.'s (2009) study, college-age students behaved in a similar manner. Kuntsche and Labhart (2012) also found that the manner in which both young men and women drank varied significantly from day to day. On Thursdays, drinking decreased over the evening; on Fridays, it did not change. But on Saturdays, drinking increased over the course of the evening. The average drinks per day went from 3 to 4 to 5.5 per night.

The environment/location

The environment clearly affects drinking behavior, for example, bar density, law enforcement, average minimum price of a drink (Gruenewald et al., 2014; Paschall et al., 2013; Zhao et al., 2013), urban versus non-urban, and low poverty urban versus high poverty urban (Davis and Grier,

2015). Demers et al. (2002), in a study of college drinkers in Canada, found that the setting had a slightly greater effect on drinking than individual characteristics. Storvoll et al. (2010), in a study of 14- to 17-year olds in Norway, found that episodes of “intoxication” occurred 50 percent of the times at home, not at bars, parties, and so on. And Senchak et al. (1998) found that college-age males got drunk more frequently when they were drinking in a large, mixed-sex group or a small, same-sex group, as opposed to a small, mixed-sex group.

Given permission to use GPS on a smartphone to track the owner's location—when combined with other factors—would probably significantly improve the accuracy and effectiveness of relapse predictions.

Sleep deprivation

It is hypothesized that sleep deprivation is one of the key factors leading to binge drinking. Sleep deprivation has an impact on neurotransmitters (Longordo et al., 2009), mood (Bernier et al., 2009), working memory (Hagewoud et al., 2009), and decision-making (Harrison and Horne, 2000). Smartphones are now able to track the quantity and, to some extent, the quality of one's sleep and to assess one's activity level. Natale et al. (2012) found that smartphones were reasonably accurate at measuring total sleep time and sleep efficiency when compared to wearing an actigraph on the wrist during sleeping. Shirazi et al. (2013) studied the use of a Somnometer. It not only tracked a person's sleep but also had the capability of sharing that information with people in one's social network.

A measure of sleep quantity and quality could be used as a measure of sleep deprivation, and smartphones have the potential to reveal for which individuals sleep deprivation may make them more vulnerable to binge drinking.

Affect

The research into the impact of affect on drinking behavior is mixed (Armeli et al., 2010; Crooke et al., 2013; Dvorak et al., 2014; Littlefield et al., 2012; Muraven et al., 2005a, 2005b; Piasecki et al., 2002; Shiffman, 2013; Vuchinich and Tucker, 1996; Witkiewitz and Villarreal, 2009). Many studies suggest that negative affect is a contributing factor to lapses and relapses but, as Dvorak and Simons (2014) note, it is a “complicated picture” (p. 976). In Dvorak and Simons (2014), high-arousal negative mood states such as anxiety but not daytime sadness (a low arousal form of negative affect) were associated with more nighttime drinking. Conversely, positive mood during the daytime was most associated with the likelihood of drinking and of heavy drinking at night. However, these are aggregated data; individuals may show distinctly idiographic patterns of affect-driven alcohol use. Dvorak et al. (2014), for example, report “considerable heterogeneity” (p. 285).

Witkiewitz and Villarroel's (2009), looking at the data from the participants in the MATCH study, found that drinking and negative affect were dynamically linked; the changes in negative affect were significantly related to the changes in prior drinking and vice versa. Specifically, non-drinking predicted reduced levels of negative affect and increased drinking predicted a greater probability of high negative affect. Those who reported higher negative affect over time had a "near-zero probability of moderate drinking" and "had the highest probability of heavy and frequent drinking" (p. 640).

Witkiewitz's (2011) secondary analysis of the COMBINE data looked to uncover the risk factors that were predictive of a lapse. She included dynamic factors, such as negative affect, craving and stress, and static factors, such as the level of dependence, marital status, and treatment history. Higher static risk predicted higher dynamic risk, and more frequent drinking also predicted higher dynamic risk, but the links were weak: "Increased dynamic risk over time were significantly associated with greater increases in heavy drinking," but "the magnitude of the effects was small" (p. 426).

Todd et al. (2009) found complex relationships between time of the day to start drinking, drinking to cope, and low and high negative affect states. For example, negative affect states were not related to the time drinking started in the early part of the day, but were in the latter part of the day, and those with stronger DTC motives were more affected by negative mood, starting to drink earlier in the day.

The probability of an episode of binge drinking may also be influenced by feedback loops leading a perhaps metastable system to quite suddenly manifest new behavior, in this case, binge drinking. In particular, the work of Witkiewitz and Villarroel (2009) supports the notion that feedback loops may create dynamic relationships between negative affect and drinking and drinking and negative affect, as do some of the studies discussed before by Muraven et al. (2005a, 2005b).

MoodScope (LiKamWa et al., 2013), as noted before, allows a user's mood to be assessed passively with a smartphone, might be used to provide a measure of an individual's affect over time. MoodScope tracks an individual's smartphone usage throughout the day, for example, location changes, application usage, SMS', phone calls, and uses that data to measure mood. Initially, the user also rates and inputs his feelings and activity level on a 5-point scale. That data, combined with general user data, help the app learn to assess mood based solely on passively collected data. After 2 months of use, their research suggests that the program is 93 percent accurate with no active input from the user. Whether MoodScope will prove an effective measure of affect remains to be seen, but it represents the kind of app that is needed. It collects data passively, uses little battery power through the day, and requires no additional equipment to be worn by the user.

Other factors

Many other factors, for example, context (cf. Kairouz et al., 2002), gender (e.g. LaBrie et al., 2011), ethnicity (Witkiewitz et al., 2011), commitment and confidence (Kuerbis et al., 2014), self-efficacy (Collins et al., 2011; Foster et al., 2013), goals and values (Cox and Klinger, 2011; Ellis, 1962; Hayes and Smith, 2005; Torre and Zoricic, 2009), supportive or non-supportive significant other (Hunter-Reel et al., 2012; O'Farrell and Fals-Stewart, 2003; Ruff et al., 2010), family history of drinking (Jackson et al., 2001), and temporal discounting (Tucker et al., 2002), may also affect predictions for a particular individual. Those factors that are hypothesized to be more or less static could be input the first time the user uses the app. Whether or not and to what degree including one or more of these factors will add predictive value is a researchable question.

Conclusion

At this point in time, using smartphones, relapse predictions that are reasonably accurate may be possible and may reduce the frequency and severity of binge drinking. To what degree this is true from individual to individual will only become evident over time and with research, but as smartphone capacities increase, predictions should improve, as has been true for the weather.

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