COMMENTARY

I Am Your Smartphone and I Know You Are About to Smoke: The Application of Mobile Sensing and Computing Approaches to Smoking Research and Treatment

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ABSTRACT

Much is known about the immediate and predictive antecedents of smoking lapse, which include situations (e.g., presence of other smokers), activities (e.g., alcohol consumption), and contexts (e.g., outside). This commentary suggests smartphone-based systems could be used to infer these predictive antecedents in real time and provide the smoker with just-in-time intervention. The smartphone of today is equipped with an array of sensors, including GPS, cameras, light sensors, barometers, accelerometers, and so forth, that provide information regarding physical location, human movement, ambient sounds, and visual imagery. We propose that libraries of algorithms to infer these antecedents can be developed and then incorporated into diverse mobile research and personalized treatment applications. While a number of challenges to the development and implementation of such applications are recognized, our field benefits from a database of known antecedents to a problem behavior, and further research and development in this exciting area are warranted.

INTRODUCTION

Cigarette smoking is a chronic relapsing disorder—over half of all smokers will attempt to quit each year, but fewer than 7% of those who quit will achieve long-term abstinence (Centers for Disease Control [CDC], 2011). Smoking lapses, which nearly always result in relapse (Kenford et al., 1994), frequently occur in situations that provoke stress and/or involve the presence of smoking-related cues or activities (Shiffman, Paty, Gnys, Kassel, & Hickcox, 1996). Cessation counseling helps smokers identify high-risk situations and provides them with strategies that can be invoked when those situations occur (e.g., relaxation, avoidance, and distraction). However, such interventions are limited by the fact that smokers are (a) required to maintain vigilance for high-risk situations and (b) remember to enact the requisite coping strategies in time to effectively avoid lapse or relapse. In this commentary, we propose for the first time that the nearly ubiquitous smartphone, with its onboard sensing and computing functions, can assist the smoker in these tasks by detecting the predictive antecedents to smoking lapse, alerting the smoker to these high-risk situations, and delivering in-time interventions.

THE IMMEDIATE AND PREDICTIVE ANTECEDENTS OF SMOKING

Our knowledge of the immediate and predictive antecedents of smoking and smoking lapses is considerable and has been informed by dozens of ecological momentary analysis (EMA) studies. In these studies, smokers are asked to indicate occurrences of smoking behavior in an electronic diary (i.e., personal digital assistant) and are then queried about the contexts, activities, and internal states that preceded smoking. EMA studies have identified a broad range of temporal (time of day and day of week), situational (presence of other smokers), activity (food/alcohol consumption, standing outside), and psychological (stress/negative affect) factors that are predictive of smoking and smoking lapses (Beckham et al., 2008; Chandra, Scharf, & Shiffman, 2011; McCarthy, Piasecki, Fiore, & Baker, 2006; Shapiro, Jamner, Davydov, & James, 2002; Shiffman et al., 1996, 2002, 2007; Shiffman, Kirchner, Ferguson, & Scharf, 2009; Shiffman, Paty, Gwaltney, & Dang, 2004) (see Table 1).

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Table 1. Example Smoking Antecedents, Their Associated Multimodal Sensory Dimensions for Fingerprinting, and Relevant Smartphone Sensors

Predictive antecedent	Sensory and other characteristics	Smartphone sensors and other information sources
Standing in a place outdoors	Location, posture, movement, and brightness	GPS, gyroscope, accelerometer, and light sensor
Traveling by vehicle	Speed, motion, and location	GPS, cell tower signals, and accelerometer
Social interaction	Speech sounds, existence of other Bluetooth/WiFi devices in the vicinity	Microphone (and speech processing), Bluetooth, and WiFi
Stress	Speech sounds, word choice, and gestures	Microphone, voice and text recognition, and visual recognition of gestures
Food/alcohol consumption	Time of day, location, ambient light and sound	Clock, GPS, WiFi SSID, accelerometer, light sensor, and microphone

Note. GPS = global positioning system; SSID = service set identifier.

COULD SMARTPHONES BE USED TO DETECT THE PREDICTIVE ANTECEDENTS OF SMOKING?

One possible yet unrealized way, in which to close the loop on knowledge gained from EMA studies would be to develop a smartphone application that detects the predictive antecedents of smoking lapse in real-time and provides just-in-time intervention. The smartphone, in addition to having onboard communications and computing functions, is equipped with a diverse array of sensors (global positioning system [GPS], cameras, microphones, Bluetooth, accelerometers, magnetometers, and gyroscopes) that can be used to provide information regarding physical location, human movement, ambient sounds, and visual imagery. Algorithms developed using signal processing and machine-learning techniques can take signals from smartphone sensors and use them to make inferences regarding real-world events. Mobile phone applications that sense and infer human behavior and context have already appeared in diverse fields including health care, transportation, safety, entertainment, and commerce (Campbell & Choudhury, 2012; Lane et al., 2010). Moreover, smartphone-based systems have been developed that detect human activity types (Hicks et al., 2010; Lu, Pan, Lane, Choudhury, & Campbell, 2009), environmental context (Azizyan, Constandache, & Choudhury, 2009), mode of transportation(Liao, Patterson, Fox, & Kautz, 2007; Thiagarajan, Biagioni, Gerlich, & Eriksson, 2010), mood (Lee, Choi, Lee, & Park, 2012; LiKamWa, Liu, Lane, & Zhong, 2011), and well-being (Lane et al., 2011).

Similar systems could be developed on the premise that many of the conditions antecedent to smoking exhibit a "fingerprint" on multiple sensing dimensions, and hence can be detected by smartphones (see Table 1). A smartphone-based system built on this premise, for instance, could warn the ex-smoker of imminent lapse when it detects she has left a bar at 10 p.m. (GPS, clock), is in the presence of others (conversation detection using the microphone), and is standing outside (accelerometer and temperature sensor) in a smoking area (visual detection of cigarette butts). The system could also record the sensed conditions or locations antecedent to smoking before an individual smoker quits. It might detect that the same smoker, now having quit, is approaching a place or context he frequently smoked (GPS, database of prequit smoking behavior) and suggest alternative routes (i.e., avoidance), unreinforced exposure to these contexts (i.e., extinction; O'Connell, Shiffman, & Decarlo, 2011), or other coping responses. Indeed, delivery of GPS-triggered interventions upon approach of patient-identified alcohol use locations has been suggested (Gustafson et al., 2011). Moreover, other, self-reported factors including urge to smoke upon waking (Shiffman et al., 1997) predict increased lapse probability during that day and their inclusion could be used to modulate system resources allocated to detecting lapse antecedents. In addition to sensing antecedents, the system could infer a lapse episode from sensed smoking behaviors including lighter ignition (acoustic signature), hand-to-mouth motion (accelerometer), and the close proximity of a lit cigarette (visual object recognition). Likewise, off-board sensors could detect physiological states associated with smoking (Plarre et al., 2011), smoking behavior itself (Lopez-Meyer, Tiffany, & Sazonov, 2012), or the presence of smoke (Liu, Antwi-Boampong, Belbruno, Crane, & Tanski, 2013) and transmit this information to the smartphone in order to infer smoking lapse.

THE CLINICAL SIGNIFICANCE OF SMARTPHONE SYSTEMS THAT DETECT SMOKING AND ITS ANTECEDENTS

Smartphone-based sensing systems, such as the one imagined here could have myriad clinical applications. For instance, mobile phone-based cessation interventions that deliver prescheduled text messages have demonstrated efficacy (Whittaker et al., 2012) but could be improved by initiating or optimizing just-in-time messages based on sensed conditions. Similarly, smartphone cessation apps are available (Abroms, Padmanabhan, Thaweethai, & Phillips, 2011) but do not include capabilities for alerting the smoker to the presence of high-risk situations. Smartphone sensing of lapse antecedents may also have application in mobile interventions including those that (a) attempt to prevent relapse following a detected lapse, (b) schedule biomarker provision and provide incentives for abstinence, and (c) prompt pharmacotherapy use in order to ward off craving/withdrawal. Beyond texting/messaging, smartphone communication and multi-media capabilities open up possibilities for a broad range of theory/evidence-based interventions (Heron & Smyth, 2010; Riley et al., 2011) including social networking/engagement (Richardson et al., 2013), cognitive training (Attwood, O'Sullivan, Leonards, Mackintosh, & Munafò, 2008), video messaging (Whittaker et al., 2011), and in situ cue-exposure treatment (Conklin & Tiffany, 2002).

SMARTPHONE SENSING FOR CONDUCTING THE NEXT GENERATION OF EMA STUDIES

In addition to clinical application, a smartphone-based system for detecting smoking, available as an app, could be used to cheaply acquire data on millions of smoking episodes from thousands of users in brief amounts of time, in otherwise remote or distant locations. Combined with data using traditional EMA methods, smartphone sensed data could be mined in order to discover previously unknown smoking antecedents, conduct surveillance of smoking at the community level, and improve lapse detection algorithms. Similar approaches to understanding real-time correlates of self-reported depression symptoms have been attempted (Burns et al., 2011) with some success. Looping back to clinical significance, with enough data, algorithms could be developed that learn which interventions result in the best outcomes for which smokers (and at what times/locations); and adaptively suggest and/or apply these interventions as needed.

CHALLENGES ASSOCIATED WITH SMARTPHONE SENSING OF SMOKING ANTECEDENTS

In addition to the engineering challenges associated with developing the library of algorithms necessary for detecting smoking and its antecedents, a number of other challenges must be addressed, including the following. (1) Continuous smartphone sensing, regardless of the application, is energy intensive, and systems must be designed that optimize the balance between detection of smoking antecedents and energy consumption. Ideas rooted in hierarchical sensing are of interest, where certain low-energy sensors (e.g., accelerometer) remain on continuous "vigil," and wake up high-energy sensors (e.g., GPS) when a relevant event seems imminent. (2) More pragmatically, smokers (like all humans) often keep their phones in locations that decrease sensor signal (e.g., in pocket/purse). The adoption of external mobile computing platforms (e.g., Google glasses) may obviate this limitation, but creative solutions will be necessary in the near term, including opportunistic sensing (e.g., when the user is checking her E-mail). (3) Additional research will be needed to determine and overcome barriers to smokers adopting a technology that senses their behavior and optimizes the usability of such systems. (4) Issues around data privacy and confidentiality will need to be addressed both from technical and ethical perspectives. (5) Very little is known regarding the effects of delivering preemptive or just-in-time interventions in the context of smoking cessation or other interventions. For instance, no algorithms will be 100% accurate, and providing interventions at the wrong time or place (i.e., false positives) could inadvertently bring smoking to mind possibly triggering an urge to smoke. Much additional research will be needed to evaluate whether implementing sensing capabilities in order to provide just-in-time interventions improves cessation outcomes and in what subgroups of smokers.

SUMMARY

We estimate there are approximately 15 million adult smokers who own a smartphone in the United States alone (CDC, 2011; Smith, 2011; US Census Bureau, 2010). Widely available and easy to distribute smartphone apps that (a) detect smoking behavior and its antecedents and (b) provide personalized, real-world, just-in-time interventions could have enormous and beneficial impact in both clinical and research fields. Whereas smartphone systems have been developed to infer other behaviors with health/safety consequences (e.g., physical activity/driving), we are fortunate as a field to know so much about the situational and contextual antecedents to a behavior of interest—these antecedents themselves can be the target of sensing. Increased research that further refines our understanding of the contextual and behavioral antecedents of smoking lapse; and the development and evaluation of novel systems that capitalize on these findings is needed. This research will necessitate building bridges between tobacco research and computer science/engineering, and we encourage the field to seek opportunities and forums to promote such collaboration.

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DECLARATION OF INTERESTS

None declared.

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