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

F. Joseph McClernon PhD[1], **Romit Roy Choudhury** PhD[2]

[1]*Division on Addiction Research and Treatment, Department of Psychiatry and Behavioral Sciences, Duke University Medical Center, Durham, NC;* [2]*Department of Electrical and Computer Engineering, Edmund T. Pratt Jr. School of Engineering, Duke University, Durham, NC*

Corresponding Author: F. Joseph McClernon, PhD, Division on Addiction Research and Treatment, Department of Psychiatry and Behavioral Sciences, Duke University Medical Center, Durham, NC 27705, USA. Telephone: 919-668-3987; Fax: 919-681-0016; E-mail: francis.mcclernon@duke.edu

Received November 20, 2012; accepted March 24, 2013

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.

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).

doi:10.1093/ntr/ntt054
Advance Access publication May 23, 2013

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.

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.

FUNDING

This work was supported by the National Institutes of Health (R21 DA034471).

DECLARATION OF INTERESTS

None declared.

REFERENCES

Abroms, L. C., Padmanabhan, N., Thaweethai, L., & Phillips, T. (2011). iPhone apps for smoking cessation: A content analysis. *American Journal of Preventive Medicine*, *40*, 279–285.

Attwood, A. S., O'Sullivan, H., Leonards, U., Mackintosh, B., & Munafò, M. R. (2008). Attentional bias training and cue reactivity in cigarette smokers. *Addiction*, *103*, 1875–1882. doi:10.1111/j.1360-0443.2008.02335.x

Azizyan, M., Constandache, I., & Choudhury, R. R. (2009). SurroundSense: Mobile phone localization via ambience fingerprinting. Paper presented at the Proceedings of the 15th Annual International Conference on Mobile Computing and Networking, Beijing, China.

Beckham, J. C., Wiley, M. T., Miller, S. C., Dennis, M. F., Wilson, S. M., McClernon, F. J., & Calhoun, P. S. (2008). Ad lib smoking in post-traumatic stress disorder: An electronic diary study. *Nicotine & Tobacco Research*, *10*, 1149–1157. doi:10.1080/14622200802123302

Burns, M. N., Begale, M., Duffecy, J., Gergle, D., Karr, C. J., Giangrande, E., & Mohr, D. C. (2011). Harnessing context sensing to develop a mobile intervention for depression. *Journal of Medical Internet Research*, *13*, e55. doi:10.2196/jmir.1838

Campbell, A., & Choudhury, T. (2012). From smart to cognitive phones. *IEEE Pervasive Computing*, *11*, 7–11.

Centers for Disease Control [CDC]. (2011). Quitting smoking among adults-united states, 2001–2010. *Morbidity & Mortality Weekly Report*, *60*, 1512–1519.

Chandra, S., Scharf, D., & Shiffman, S. (2011). Within-day temporal patterns of smoking, withdrawal symptoms, and craving. *Drug and Alcohol Dependence*, *117*, 118–125.

Conklin, C. A., & Tiffany, S. T. (2002). Applying extinction research and theory to cue-exposure addiction treatments. *Addiction*, *97*, 155–167. doi:10.1046/j.1360-0443.2002.00014.x

Gustafson, D. H., Shaw, B. R., Isham, A., Baker, T., Boyle, M. G., & Levy, M. (2011). Explicating an evidence-based, theoretically informed, mobile technology-based system to improve outcomes for people in recovery for alcohol dependence. *Substance Use & Misuse*, *46*, 96–111. doi:10.3109/10826084.2011.521413

Heron, K. E., & Smyth, J. M. (2010). Ecological momentary interventions: Incorporating mobile technology into psychosocial and health behaviour treatments. *British Journal of Health Psychology*, *15*(Pt. 1), 1–39. doi:10.1348/135910709X466063; bjhp696 [pii]

Hicks, J., Ramanathan, N., Kim, D., Monibi, M., Selsky, J., Hansen, M., & Estrin, D. (2010). AndWellness: An open mobile system for activity and experience sampling. Paper presented at the Wireless Health 2010, San Diego, CA.

Kenford, S. L., Fiore, M. C., Jorenby, D. E., Smith, S. S., Wetter, D., & Baker, T. B. (1994). Predicting smoking cessation. Who will quit with and without the nicotine patch. *Journal of the American Medical Association*, *271*, 589–594.

Lane, N. D., Miluzzo, E., Lu, H., Peebles, D., Choudhury, T., & Campbell, A. T. (2010). A survey of mobile phone sensing. *IEEE Communications Magazine*, *48*, 140–150. doi:10.1109/Mcom.2010.5560598

Lane, N. D., Mohammod, M., Lin, M., Yang, X., Lu, H., Ali, S., … Campbell, A. T. (2011). BeWell: A smartphone application to monitor, model and promote wellbeing. Paper presented at the 5th International ICST Conference on Pervasive Computing Technologies for Healthcare, Dublin, Ireland.

Lee, H., Choi, Y. S., Lee, S., & Park, I. P. (2012). Towards unobtrusive emotion recognition for affective social communication. Paper presented at the IEEE Consumer Communications and Networking Conference, Las Vegas, NV.

Liao, L., Patterson, D. J., Fox, D., & Kautz, H. (2007). Learning and inferring transportation routines. *Artificial Intelligence*, *171*, 311–331.

LiKamWa, R., Liu, Y., Lane, N. D., & Zhong, L. (2011). Can your smartphone infer your mood? Paper presented at the PhoneSense 2011 Conference, Seattle, WA.

Liu, Y., Antwi-Boampong, S., Belbruno, J. J., Crane, M. A., & Tanski, S. E. (2013). Detection of secondhand cigarette smoke via nicotine using conductive polymer films. *Nicotine & Tobacco Research*. doi:10.1093/ntr/ntt007

Lopez-Meyer, P., Tiffany, S., & Sazonov, E. (2012). Identification of cigarette smoke inhalations from wearable sensor data using a Support Vector Machine classifier. *Conference Proceedings: Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, 2012, 4050–4053. doi:10.1109/EMBC.2012.6346856

Lu, H., Pan, W., Lane, N. D., Choudhury, T., & Campbell, A. T. (2009). SoundSense: Scalable sound sensing for people-centric applications on mobile phones. Paper presented at the Proceedings of the 7th International Conference on Mobile Systems, Applications, and Services, Kraków, Poland.

McCarthy, D. E., Piasecki, T. M., Fiore, M. C., & Baker, T. B. (2006). Life before and after quitting smoking: An electronic diary study. *Journal of Abnormal Psychology*, *115*, 454–466. doi:10.1037/0021-843X.115.3.454

O'Connell, K. A., Shiffman, S., & Decarlo, L. T. (2011). Does extinction of responses to cigarette cues occur during smoking cessation? *Addiction*, *106*, 410–417. doi:10.1111/j.1360-0443.2010.03172.x

Plarre, K., Raij, A., Hossain, M., Ali, A., Nakajima, M., al'Absi, A., … Wittmers, L. (2011). Continuous inference of psychological stress from sensory measurements collected in the natural environment. Paper presented at the Information Processing in Sensor Networks, Chicago, IL.

Richardson, A., Graham, A. L., Cobb, N., Xiao, H., Mushro, A., Abrams, D., & Vallone, D. (2013). Engagement promotes abstinence in a web-based cessation intervention: Cohort study. *Journal of Medical Internet Research*, *15*, e14. doi:10.2196/jmir.2277

Riley, W. T., Rivera, D. E., Atienza, A. A., Nilsen, W., Allison, S. M., & Mermelstein, R. (2011). Health behavior models in the age of mobile interventions: Are our theories up to the task? *Translate Behavioral Medicine*, *1*, 53–71. doi:10.1007/s13142-011-0021-7

Shapiro, D., Jamner, L. D., Davydov, D. M., & James, P. (2002). Situations and moods associated with smoking in everyday life. *Psychology of Addictive Behaviors*, *16*, 342–345. doi:10.1037/0893-164X.16.4.342

Shiffman, S., Balabanis, M. H., Gwaltney, C. J., Paty, J. A., Gnys, M., Kassel, J. D., … Paton, S. M. (2007). Prediction of lapse from associations between smoking and situational antecedents assessed by Ecological Momentary Assessment. *Drug and Alcohol Dependence*, *91*, 159–168.

Shiffman, S., Engberg, J. B., Paty, J. A., Perz, W. G., Gnys, M., Kassel, J. D., & Hickcox, M. (1997). A day at a time: Predicting smoking lapse from daily urge. *Journal of Abnormal Psychology*, *106*, 104–116.

Shiffman, S., Gwaltney, C. J., Balabanis, M. H., Liu, K. S., Paty, J. A., Kassel, J. D., … Gnys, M. (2002). Immediate antecedents of cigarette smoking: An analysis from Ecological Momentary Assessment. *Journal of Abnormal Psychology*, *111*, 531–545. doi:10.1037/0021-843X.111.4.531

Shiffman, S., Kirchner, T. R., Ferguson, S. G., & Scharf, D. M. (2009). Patterns of intermittent smoking: An analysis using Ecological Momentary Assessment. *Addictive Behaviors*, *34*, 514–519.

Shiffman, S., Paty, J. A., Gnys, M., Kassel, J. A., & Hickcox, M. (1996). First lapses to smoking: Within-subjects analysis of real-time reports. *Journal of Consulting and Clinical Psychology*, *64*, 366–379. doi:10.1037/0022-006X.64.2.366

Shiffman, S., Paty, J. A., Gwaltney, C. J., & Dang, Q. (2004). Immediate antecedents of cigarette smoking: An analysis of unrestricted smoking patterns. *Journal of Abnormal Psychology*, *113*, 166–171. doi:10.1037/0021-843X.113.1.166

Smith, A. (2011). *Smartphone adoption and usage*. Washington, DC: Pew Internet & American Life Project.

Thiagarajan, A., Biagioni, J., Gerlich, T., & Eriksson, J. (2010). Cooperative transit tracking using smart-phones. Paper presented at the Proceedings of the 8th ACM Conference on Embedded Networked Sensor Systems, Zürich, Switzerland.

US Census Bureau. (2010). Profile of general population and housing characteristics: 2010. Retrieved from http://factfinder2.census.gov/faces/tableservices/jsf/pages/productview.xhtml?pid=DEC_10_DP_DPDP1

Whittaker, R., Dorey, E., Bramley, D., Bullen, C., Denny, S., Elley, C. R., … Salmon, P. (2011). A theory-based video messaging mobile phone intervention for smoking cessation: Randomized controlled trial. *Journal of Medical Internet Research*, *13*, e10. doi:10.2196/jmir.1553

Whittaker, R., McRobbie, H., Bullen, C., Borland, R., Rodgers, A., & Gu, Y. (2012). Mobile phone-based interventions for smoking cessation. *Cochrane Database of Systematic Reviews*, *11*, CD006611. doi:10.1002/14651858.CD006611.pub3