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The Use of Ambulatory Assessment in Smoking Cessation

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Abstract

Ambulatory assessment of smoking behavior has greatly advanced our knowledge of the smoking cessation process. The current article first provides a brief overview of ecological momentary assessment for smoking cessation and highlights some of the primary advantages and scientific advancements made from this data collection method. Next, a discussion of how certain data collection tools (i.e., smoking topography and carbon monoxide detection) that have been traditionally used in lab-based settings are now being used to collect data in the real world. The second half of the paper focuses on the use of wearable wireless sensors to collect data during the smoking cessation process. Details regarding how these sensor-based technologies work, their application to newer tobacco products, and their potential to be used as intervention tools are discussed. Specific focus is placed on the opportunity to utilize novel intervention approaches, such as Just-In-Time Adaptive Interventions, to intervene upon smoking behavior. Finally, a discussion of some of the current challenges and limitations related to using sensor-based tools for smoking cessation are presented, along with suggestions for future research in this area.

Keywords

ambulatory assessment; smoking cessation; wearable technology

The ambulatory assessment of smoking behavior has greatly evolved over the last several decades and continues to do so through advances in technology. The data gathered via ambulatory assessment has the potential to not only contribute to the development of

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efficacious cessation interventions, but also to the larger theoretical literature on smoking behavior and relapse. Ambulatory assessment can aid in “filling in the blanks” regarding what happens in a real-world setting (i.e., outside of the laboratory) prior to an individual picking up a cigarette to smoke. These data are vital to advancing theories on smoking relapse, as the current state of our models provide little guidance on the complex temporal patterns of mood and relapse, and the general relationships that exist moment-to-moment among key relapse variables. For example, we know motivation is a key factor in behavior change and that individuals may change their intentions to quit smoking on a daily basis (Hughes, Keely et al., 2005; Hughes, Solomon et al., 2013; Peters & Hughes, 2009). However, we do not have strong theoretical models to guide how an intervention should be developed and implemented based on these daily, or even more frequent, motivational fluctuations in order to prevent relapse. Further, it is not clear how other key variables in the cessation process (e.g., negative affect, self-efficacy) may influence or be changed by a momentary intervention targeting motivation. As such, collecting and examining data via ambulatory assessment provides the opportunity to inform theoretical models of change for smoking cessation that will have implications for relapse prevention.

Aside from theory, ambulatory assessment can have a direct impact on intervention development. For example, although we know that negative affect is a key trigger for relapse, it is not clear how fluctuations in negative affect may interact with an individual's self-efficacy for quitting. If a cessation intervention is able to slowly increase self-efficacy for quitting over the first few days of a quit attempt, will a spike in negative affect on day 3 of the quit attempt be a huge risk for relapse? Should the intervention also target negative affect? If so, does the timing of delivery of the negative affect component of the intervention matter? Capturing how these variables interact and shift hour-to-hour, minute-to-minute via advances in ambulatory assessment will allow us to intervene at the most opportune time to prevent relapse. Much of this future work will be shaped by advances in technology, including the ability to monitor and intervene upon behavior via wearable devices.

This paper will provide a brief overview of the history of ambulatory assessment as related to smoking behavior with a primary emphasis on smoking cessation, as many other papers have described this topic in great detail (Shiffman, 2014; Shiffman, Stone, & Hufford, 2008; Stone & Shiffman, 1994). The paper then shifts to discuss current and future applications of ambulatory assessment, with a particular focus on the role of wearable sensors and its potential to influence how smoking behavior is captured and intervened upon.

Ecological Momentary Assessment

Early research on smoking behavior and cessation primarily relied on retrospective recall at clinic visits. That is, participants would attend an in-person clinic visit and be asked something along the lines of “What caused you to lapse?” or “What was your mood like when you lapsed?” Although these data provided insight into the smoking cessation process, the limitations of retrospective recall are numerous. Previous work has discussed these issues in detail (Shiffman et al., 2008). One method for addressing the limitations of studies that rely on retrospective recall is to use ecological momentary assessment (EMA). EMA consists of a variety of methods designed to assess phenomena closer to real time in the real

world by having participants monitor their daily activities (Shiffman, 2009). Two commonly used forms of EMA in the smoking cessation literature are daily diary studies and studies that consist of multiple daily assessments. It should be noted that daily diary studies are sometimes captured under other terms used to describe ambulatory assessments (e.g., experience sampling). Here we have decided to discuss daily diaries under the umbrella of EMAs, consistent with the EMA tobacco use literature (Shiffman et al., 2008; Shiffman, 2009).

Daily diary studies usually involve asking participants to complete a set of questions one time per day, and data may be collected in a paper and pencil format or through prompts sent on a smartphone. Diaries are typically completed at the same time of day for the duration of the study, and ask participants various questions that may summarize their day (e.g., How many cigarettes did you smoke today? Rate your level of sadness over the past 24 hours.). These questions may be asked over several days or weeks to capture what is occurring on a daily basis during the smoking cessation process.

Another type of EMA design involves having participants report their current behavior multiple times per day. Data are often collected via a hand held device (e.g., smartphone) by sending participants multiple prompts throughout the day. A much richer source of data is gathered through this design relative to others (i.e., daily diary, longitudinal, and cross-sectional), as the ability to prospectively examine within-person changes in variables important to smoking within the same day becomes available (Lam, et al., 2014; Vinci et al., 2017).

Smoking Topography and Carbon Monoxide

Other types of ambulatory assessment somewhat unique to the field of smoking include the collection of smoking topography and carbon monoxide. Smoking topography involves measuring smoking behavior by having the participant smoke a cigarette through a smoking topography device. The device stores data such as number of puffs taken, time to smoke a puff, interpuff intervals, puff duration, puff velocity, and puff volume (CReSS; Plowshare Technologies, Baltimore, MD, USA). Smoking topography studies provide useful information on the relationship between smoking behavior and smoking cessation, and topography has been measured in settings outside of the laboratory. Prior work has examined smoking topography in the real world to determine differences in smoking patterns among groups of people (e.g., chippers vs dependent smokers; Brauer, 1996; Korean American vs White men; Chung, Kim, Kini, Fang, Kalman, & Ziedonis, 2015). Research has also shown that self-reported cigarettes smoked per day were not associated with smoking topography patterns in day-to-day life (Hatsukami, Morgan, & Pickens, 1987). That is, people who reported smoking more cigarettes per day did not necessarily demonstrate more intense smoking behavior via topography device in the real world, and vice versa. Such findings have multiple implications, including the applicability to withdrawal symptoms experienced during a quit attempt, as people who smoke more cigarettes per day may not necessarily be more physically dependent on tobacco.

Measuring level of carbon monoxide (CO) in smoking cessation studies is a valuable source of objective data regarding abstinence outcomes. For instance, the seven day point prevalence of smoking is commonly used as an abstinence outcome in cessation studies, which is the self-report of no smoking in the past seven days, combined with a CO reading of less than some predefined level of CO in parts per million (ppm; Benowitz et al., 2002). Although CO readings are typically conducted in-person at clinic visits, mobile, phone-based CO readers have been developed (Meredith, Robinson, Erb, Spieler, Klugman, Dutta, & Dallery, 2014). The ability to use a portable CO monitor can greatly reduce participant burden of traveling to the clinic during cessation studies to confirm abstinence status. Further, Meredith and colleagues (2014) found that this device was rated as highly useable and acceptable among their sample of participants, which were low socioeconomic status (SES) smokers (i.e., majority with no college education and an income of less than \$200 per month). Although an initial concern of mobile CO readers may be the inability to confirm who submitted the sample, Dallery and colleagues (2013) have developed a web-based application that allows individuals to take CO readings at home, all while monitoring the process via webcam to confirm that the correct person has provided the sample. In fact, this technology has been taken one step further to allow for mobile-based CO readings that also have a video component to confirm the user (Hertzberg et al., 2013). Initial findings have deemed compliance to this technology as excellent (Hertzberg et al., 2013).

Wireless Wearable Sensors

As ambulatory assessment has continued to advance, there has been an increase in the development of wearable wireless sensors. These devices are worn somewhere on the body, such as the wrist, ankle, or chest. Although a variety of sensors have been developed for the measurement of a multitude of behaviors, this section primarily focuses on those specific to smoking behavior. The detection of smoking behavior in the real world in real time is incredibly important when studying smoking lapse and relapse. Prior to wearable sensors, researchers had to rely on participant self-report of smoking. However, recent developments in technology have allowed the objective and unobtrusive detection of smoking behavior without participant volition (i.e., the participant self-reporting their smoking status).

An example of wearable wireless sensors is AutoSense (Ertin et al., 2011). AutoSense consists of a chest band that detects physiological measures of electrocardiogram (ECG), respiration, galvanic skin response, skin temperature, and accelerometer data from participants. Real time smoking behavior can be estimated when the data from these sensors is combined with data collected from wrist-worn sensors (that detect hand-to-mouth movement when smoking) using machine learning algorithms. *puffMarker* is a recent model that uses data from both AutoSense (detecting deep inhalation and exhalation pattern) and wrist sensors (to identify hand to mouth gestures around deep inhalation and exhalation) to identify smoking behavior (Saleheen et al., 2015). *puffMarker* most recently reported a sensitivity rate of 96.9% and a false positive rate of 1.1% for smoking detection (Saleheen et al., 2015). In the development of *puffMarker*, an analysis of when participants self-reported a lapse via smartphone, compared to when *puffMarker* detected a lapse, was conducted (lapse status was confirmed using a CO monitor during daily lab visits). Of those people *puffMarker* identified as having lapsed ($n = 28$), 54% of participants self-reported that the

lapse occurred an average of 41 minutes after *puffMarker* detected the smoking episode. About 14% reported the lapse occurring an average of 12 minutes before *puffMarker* detected the episode, and another 32% did not report the lapse as occurring at all (Salaheen et al., 2015). When attempting to examine acute, temporal relationships among key variables related to lapse, these data present an issue, as they suggest that not only can the timing of lapse reporting be inaccurate, but also that relying on participants to ever report the lapse in the first place is problematic. Thus, the objective, unobtrusive detection of smoking behavior has the ability to greatly advance the understanding of the smoking cessation process, as researchers will be able to detect the exact moment when someone smokes a cigarette. When combined with self-report data collected via EMA (e.g., mood, other people smoking, location), these data have the ability to greatly inform treatment interventions that can target specific variables related to lapse and relapse (discussed in more detail below).

Increased negative affect has been cited as one of the most common precipitants of smoking relapse (Brandon, 1994; Brandon, Tiffany, Obremski, & Baker, 1990; Lam et al., 2014; Shiffman & Waters, 2004; Shiffman, 1982; Shiffman et al., 1996). To date, negative affect has been primarily captured through self-report. A recently developed model, *cStress* can detect the experience of negative affect¹ from physiological data (Hovsepian et al., 2015). *cStress* uses the AutoSense suite described above to collect several physiological indicators of negative affect that include ECG and respiration data. In the laboratory, *cStress* has a sensitivity rating of 89% and a false positive rate of 5% for negative affect (Hovsepian et al., 2015). *cStress* has been tested in several independent field studies against self-reported stress. Median correlations between *cStress* and self-reported negative affect range from .65 to .72 (Hovsepian et al., 2015; Sarker et al., 2016; Sarker et al., in press). The ability to assess negative affect, without relying on participant self-report, allows observation of both the natural course of negative affect and its association with lapse. A better understanding of this process can assist in developing interventions that target negative affect, a primary trigger of smoking relapse, within moments of experiencing it. Importantly, *cStress* not only has application to smoking cessation, but also to other health behaviors where negative affect is a primary component.

Although highlighted above are some specific types of ambulatory assessment technologies, other research teams have been working on similar devices (Gimpel, Regal, & Schmidt, 2015; Gjoreski, Gjoreski, Lusterk, & Gams, 2016; Kostopoulos, Kyritses, Deriaz, & Konstantas, 2016; Lopez-Meyer, Tiffany, & Sazonov, 2012; Parate, Chiu, Chadowitz, Ganesan, & Kalogerakis, 2014; Tang, Vidrine, Crowder, & Intille, 2014; Varkey, Pompili, & Walls, 2011). For instance, to detect smoking behavior, *RisQ* utilizes sensors within wristbands only and findings show that smoking detection is high with a 95.7% accuracy rating in overall gesture recognition for smoking (i.e., percentage of identified smoking gestures), 91% precision rate in detecting smoking gestures (i.e., percentage of correctly

¹*cStress* (which measures physiology) was trained on data collected in a lab-based study where participants completed three stressor tasks, and was then validated in a one-week field study. When wearing the equipment in both studies, participants reported their experience of affect according to 5 questions assessing emotions such as happy, angry, and sad. In the field study, data collected via *cStress* was correlated at .72 with the report of negative affect. Thus, *cStress* detects physiological stress, which was shown to be highly correlated with the self-report of negative affect. To be consistent with the extant smoking literature, we chose to use the term negative affect here instead of stress. However, the reader should be aware of this distinction between the self-report of negative affect and physiological stress in the validation of *cStress*.

identified smoking gestures among all smoking events), and 81% recall rate (i.e., the percentage of all smoking behaviors that were correctly labeled); these data were pulled from a total of 5597 gestures, 369 of which were smoking puffs (Parate et al., 2014). These initial findings are promising, as the detection of smoking behaviors via only wristband greatly decreases participant burden. Smokebeat is a smartphone application that is being piloted to detect smoking behavior by examining hand-to-mouth gestures detected via wristband only (Dar, 2017). Varkey and colleagues (2011) are studying a wearable system that detects a variety of “on the fly” behaviors (e.g., jogging, writing, standing) that includes smoking behavior.

Regarding the detection of negative affect (as well as general stress), several teams are developing and testing various technology-based products. For instance, researchers are in the process of developing models that detect stress from data collected through only wrist devices (Microsoft Band) in the general, non-smoking population (Gjoreski et al., 2016). This wrist device collects physiological data (e.g., heart rate, galvanic skin response) and accelerometer data, which is integrated on a smartphone. Results showed that following data collection over 55 days, the ability to detect stress in the real world was 92% (Gjoreski et al., 2016). Facial expression recognition via the camera on a smartphone is also in development, as a way to detect whether an individual is experiencing one of the six basic emotions (anger, disgust, fear, sadness, happiness, and surprise; Suk & Prabhakaran, 2014). This type of technology has the ability to provide a richer set of data regarding emotional experience and how specific emotions are related to behaviors such as smoking lapse. Other teams have been developing technology that collects data from multiple sources to detect stress. For instance, StayActive gathers data from people’s daily smartphone usage, with specific focus on sleeping patterns, social interactions, and physical activity (Kostopoulos et al., 2016). A stress detection algorithm is designed for each user to determine daily stress level. Model development for this system is ongoing. Another system, myStress, is currently being developed to derive stress level from data collected via 36 hardware and software sensors from a smartphone (e.g., calendar events, notifications, weather, audio frequency, voice analysis, screen switching, text information); this system aims to collect all data exclusively via smartphone, which would greatly decrease the need for user input (Gimpel et al., 2015). It should be noted that commercially-available sensors do exist; however, given the lack of peer-reviewed published data on these devices, we do not further discuss them here.

Data collected through Global Positioning System (GPS) provides unique opportunities to link the location of an individual to their smoking behavior. Previous work has identified several neighborhood-level contextual precipitants to smoking relapse, such as residential proximity to smoking outlets and unemployment (Kendzor et al., 2012; Reitzel et al., 2011). GPS can extend this research on environmental predictors of relapse, to actually track participants’ locations throughout the day, and then link these data to lapse and relapse. For instance, data has shown that tobacco advertising is more common in low SES neighborhoods (Laws, Whitman, Bowser, & Krech, 2002), and it is likely that exposure to such advertising may increase craving among someone attempting to quit smoking. Data collected via GPS and EMA could elucidate such a relationship between exposure to tobacco advertising and craving, and subsequently determine risk for lapse and relapse. Such

data provide insight into how the external environment may impact the ability to quit smoking, and subsequently provide opportunities for intervention.

It should be briefly noted that wearables to detect other health-risk behaviors are quickly advancing. For example, the National Institute on Alcohol Abuse and Alcoholism has had two competitions related to the development of wearable alcohol biosensors to detect blood alcohol content. Activity monitors, such as the Fitbit and ActiGraph, are examples of technology being utilized to gather objective data on steps (Gusmer, Bosch, Watkins, Ostrem, & Dengel, 2014; Paul et al., 2015; Takacs, Pollock, Guenther, Bahar, Napier, & Hunt, 2014), whereas objective data collected on sleep and heart rate with these devices are ongoing (Meltzer, Hiruma, Avis, Montgomery-Downs, & Valentin, 2015; Rosenberger, Buman, Haskell, McConnell, & Cartensen, 2016; Wang et al., 2017).

Data collected through wireless wearable sensors circumvent some issues found with EMA methods. The need to rely solely on participant volition is greatly reduced (for instance, the self-report of smoking behavior and negative affect is not needed when using AutoSense and wrist sensor data). Further, some aspects of noncompliance, such as participants not responding to prompts on their phone, are also removed.

Opportunities for Intervention Development via Wearables

As ambulatory assessment advances to include wearables, the ability to intervene upon behavior with greater accuracy and precision (e.g., determining when someone is experiencing high negative affect vs no negative affect at a particular moment in time) also improves. Just-In-Time Adaptive Interventions (JITAI) use decision rules that link real time data (often collected via sensors) to the timing, type, and content of intervention strategies implemented through a smartphone (Nahun-Shani, Smith, Tewari, Witkiewitz, Collins, Spring, & Murphy, 2014; Spruijt & Nilsen, 2014). JITAI tailor the timing and selection of intervention options to specific situations and to the needs of a particular individual. They rely on the detection of a behavior/event/mood, in order to accurately intervene upon it. This detection can be something initiated by the user (e.g., the user indicates the need for support by pressing a button on the phone), or unobtrusively via sensors. Wearable technology not only provides the opportunity for the detection of smoking and negative affect in an objective and unobtrusive manner, but also other behaviors such as eating, drinking, geospatial risks, and so on. As such, cessation interventions can capitalize on relevant smoking triggers as precipitants of smoking lapse. For example, if the sensors detect high levels of negative affect at a given moment, stress management strategies can be sent to participants via smartphone at that same time. In the event that someone does lapse, interventions can be provided prior to that individual progressing to full relapse. Regarding data collected via GPS, mobile interventions can be sent to participants if they are within certain proximity of a tobacco outlet or some other environmental trigger for use. With the advancement of technology, the ability to intervene upon those experiences most critical to relapse for a particular individual can improve. Furthermore, providing treatment via JITAI may allow increased access to care for those unable to attend regular visits with a healthcare provider (due to lack of transportation, financial issues, etc.), increasing the reach of cessation interventions.

Although we are not aware of any published studies looking at the efficacy of JITAIs for smoking cessation that utilize wearable sensors, one paper has published feasibility data on a trial using a JITAI for cessation (Naughton et al., 2016). Two important findings from this study were that geofencing was reliable and accurate for identifying smoking locations, and participants' reaction to receiving supportive cessation messages, based on their location, were positive.

Other areas of substance use have implemented JITAIs via wearable wireless sensors. For instance, the A-CHESS intervention was delivered via smartphone to individuals with an alcohol use disorder upon discharge from residential treatment to aid in the prevention of relapse (Gustafson et al., 2014). The A-CHESS intervention consisted of static content on the phone that the participants could access at their leisure, as well as content that was based on participant behavior. For example, if participants entered a high-risk location (such as a previous bar he/she would frequent), their phone would ask the participant if he/she wanted to be there. Participants also completed a weekly measure of risky drinking behavior, and these data could be made available to the participant's counselor. Counselors were able to review and provide feedback to participants based on their score. Findings indicated that participants in the A-CHESS group reported significantly fewer risky drinking days over the 8 months of the intervention and through the 4-month follow-up when compared to the treatment as usual group.

The A-CHESS study has the ability to inform potential JITAIs for smoking cessation. When combining various types of data collected via wearable wireless sensors, JITAIs can take advantage of multiple sources of information to intervene upon smoking behavior. For instance, a JITAI might be designed to detect the following variables within a smoking cessation attempt: current location status (collected via GPS), negative affect (collected via chest band measuring ECG and respiration) and alcohol use (collected via a patch or sensor that detects blood alcohol level). The sensors may detect that at 1:40pm the individual had a negative affect episode, followed by detecting a blood alcohol level of .07 at 2:30pm. The individual is then detected as being within 50 yards of a tobacco outlet at 3:00pm. When developing a JITAI, the researcher determines when an intervention may be delivered. In this example, it may have been decided that at any time, the detection of negative affect, alcohol use, or being within 50 yards of a tobacco outlet would trigger an intervention delivery to be sent via smartphone. On the other hand, it could be decided that a combination of two or more triggers within a pre-determined amount of time would trigger an intervention. If negative affect and alcohol use occurred within the same hour, for instance, then an intervention would be triggered. Aside from determining when an intervention is delivered, the type of intervention sent is also important. The researcher may decide that going within 50 yards of a tobacco outlet would result in a text message suggesting that the participant either not go into the store, or prepare themselves prior to entering. The detection of negative affect may result in specific stress management techniques sent to a participant to use in that moment. Alcohol use may trigger messages sent to the participant that provide information related to alcohol being a high risk trigger for smoking lapse. This example highlights several key aspects of a JITAI including the ability to detect specific behaviors, the unique opportunity to intervene at specific moments to prevent lapse, the variety of interventions that can be delivered, and that all of this can be done without relying on participant self-

report. That said, EMA could capture particular information that a JITAI may also target (e.g., craving, self-efficacy).

Challenges and Limitations of Wearables

Although wearable technology provides great opportunity for the better understanding of mechanisms of behavior and for the development of interventions for health-risk behaviors, there are still some challenges and limitations associated with collecting these types of data. One challenge involves the ability to accurately detect the behavior being measured. For instance, the motion of the arm when smoking a cigarette can mimic that used for eating food or drinking. Physical activity can also create noise in the data, as the arousal from physical activity (e.g., increased heart rate and respiration) can mimic that of negative affect. Addressing such confounds are necessary to make sure the detection of smoking and negative affect is accurate.

A second challenge to the development, design, and implementation of research that utilizes wearable wireless sensors is the need for a team science approach. Accurately capturing and intervening upon health risk behaviors through technology requires a multidisciplinary team of behavioral scientists, engineers, computer scientists, statisticians, and others. Although it can be exciting to form such collaborations, some common issues can arise such as: understanding the needs of other disciplines, learning how to communicate your needs and goals to people in other disciplines (e.g., terminology can vary greatly), understanding that working with new technology can take more time than anticipated, and communicating about authorship and publications. Although there are challenges associated with a team science approach, one of the great benefits is the ability to combine areas of expertise to design and implement interventions that might not have been possible otherwise. For additional information on team science that is beyond the scope of this article, the following papers provide a wider perspective of the science of team science, including common definitions, the role of leadership, importance of collaboration, and the actual study of team science: Borner et al., 2010; Fiore, 2008; Stokols, Hall, Taylor, & Moser, 2008.

Third, machine learning and new statistical approaches are often necessary when working with wearables. Although a challenge, this issue is not new. As data collection advanced from in-person clinic visits to EMA approaches for smoking, new ways to conceptualize, analyze, and report data were necessary (Stone & Shiffman, 2002). For wearable sensors, machine learning models are necessary due to the complexity of the data gathered. Dynamic prediction modeling is one type of statistical approach that can be used to model complex temporal associations among multiple real time constructs (Nicholaie, Houwelingen, Witte, & Putter, 2013; Rizopoulos, 2011; van Houwelingen & Putter, 2008; van Houwelingen, 2007; van Houwelingen, 2011). When applied to smoking, this modeling can predict elevated risk of lapses ahead of time, while also updating the prediction of lapse as time progresses and more recent data become available for a particular individual. Finally, the machine learning algorithms used to detect negative affect or smoking are only as good as the training data used, and may not reflect all participants across all populations in all situations.

Limitations of wearable wireless sensors should be noted. Although participant volition is no longer an issue (i.e., the participant does not have to self-report smoking status or negative affect), participants still have to wear the equipment and do so properly. For instance, a smoking event will be missed if the participant is not wearing the equipment at that time. As such, this can be burdensome, so more compensation is often needed to maintain compliance than would be provided in EMA studies. However, technology continues to rapidly develop and the ability to detect smoking behavior and other high-risk situations less obtrusively, with little to no reliance on the participant having to self-report behavior, and with minimal issues related to compliance will continue to improve (Gimpel et al., 2015; Gjoreski et al., 2016; Kostopoulos et al., 2016; Suk & Prabhakaran, 2014). Further, the look and style of wearables continues to develop, such that some devices are becoming smaller and even fashionable (e.g., smartwatches, bracelets). Therefore, concerns regarding participant compliance and the need to compensate for participation may be lessened as the field moves forward. Interventions delivered via wearables have the potential to increase awareness of smoking triggers, which could increase urges to smoke. In prior work, participants have indicated that although just-in-time messages made them aware of smoking, they were usually thinking of smoking most of the time already (Naughton et al., 2013; Naughton et al., 2016). As technology continues to advance in intervention development and delivery, future work will want to empirically test this possibility.

We often do not confirm who is wearing the sensors at a given time, although this is something that can likely be done if wanted (e.g., thumbprint access to unlock phone). Additional ways to circumvent this issue include having study staff explain the importance of not allowing other people to wear the equipment, and making sure that compensation is not linked to what the equipment is detecting (unless the study is contingency-management based) in order to decrease the likelihood that the participant will have another person wear it. As noted above, a challenge of wearables is how accurately the behavior is being captured. In order to capture good quality data, participants must wear the equipment properly. Thus, a component of the study protocol must be to train participants on the technology itself, and to have research staff readily available to problem-solve any issues with participants throughout the study. Even if good quality data can be collected, the machine-learning models are not perfect and may miss detecting the event and sometimes may provide false detections. Technology-related issues can also arise, as data may be lost in wireless transmission, or the stored data could be lost due to device malfunction.

Another limitation is that due to the use of advanced technology, some individuals may struggle with participating if they have limited or no familiarity with the devices. For example, individuals who have never used a smartphone may have difficulty learning to navigate the phone applications. Although training is highly recommended as a component of these studies, participants are usually expected to have some basic knowledge on the use of a smartphone. Researchers should consider assessing familiarity with smartphones if using them in their studies. Unless much training is provided, it is unlikely that someone with no smartphone experience will be able to quickly pick up the necessary skills in such a short time frame. Unfortunately, excluding these individuals from smoking cessation studies can be viewed as a huge limitation, as individuals with low SES are more likely to have difficulty quitting smoking (Barbeau, Krieger, & Soobader 2004; Centers for Disease

Control and Prevention, 2015), and at the same time have low rates of smartphone ownership compared to those with high SES (Pew Research Center, 2016). Finally, the costs associated with conducting research with wearables can be high, as you must account for purchasing the equipment/software, the time and staff needed to train participants, and participant compensation. Despite these limitations, wireless sensors complement other prevalent measurement approaches. In particular, they provide a new capability that did not exist previously, namely, pinpointing the timing of behaviors of interest (e.g., smoking) without depending on participant initiation (for self-reporting the event or putting a device on prior to the event).

Future Research/Next steps

The application of ambulatory assessment to new nicotine products will be an exciting avenue for future research. For example, e-cigarettes are a newer nicotine product on the market, and the use of this product has been rapidly increasing in recent years, with about one-third of current cigarette smokers endorsing e-cigarette use (King, Alam, Promoff, Arrazola, & Dube, 2013; McMillan, Gottlieb, Shaefer, Winickoff, & Klein, 2015). Two major research questions surrounding e-cigarettes that may be answered via ambulatory assessment are: Can they be used as a smoking cessation tool, and how often are they being used by youth (i.e., to better assess patterns of use by youth)? Patterns of dual use (the use of both e-cigarettes and combustible cigarettes) could also be better understood through future research. EMA methods will be a great tool to learn more about the patterns of e-cigarette use, as these data will allow for the elucidation of momentary relationships among e-cigarette use patterns and associated mood, social factors, and contextual/environmental antecedents. Multiple studies have indicated that when compared to the topography of combustible cigarettes, individuals who smoke e-cigarettes take longer and slower puffs (Evans & Hoffman, 2014; Lee, Gawron, & Goniewicz, 2015; Spindle, Breland, Karaoghlanian, Shihadeh, & Eissenberg, 2015; Talih et al., 2015). Similar to *puffMarker*, the development of a sensor-based technology to capture when an e-cigarette is being smoked (as opposed to a combustible cigarette) would even further advance knowledge of e-cigarette and dual use.

Although ambulatory assessment methods provide an exciting next step in the application of technology to health behaviors, there is not yet a thorough understanding of how people will respond to interventions provided via wearables and smartphones. For instance, recent findings from the IDEA study found that individuals who were randomized to the wearable device group lost less weight over 24 months (i.e., were less successful in losing weight) when compared to those who did not wear such devices (Jakicic et al., 2016). This finding was counterintuitive to what was expected, as one would anticipate that those in the wearable device group would have better weight loss results. Research utilizing ambulatory assessment should query participants at the end of the study to get their feedback on the devices used. This is particularly important when the technology and/or intervention being delivered is novel to the participants.

To date, numerous trials testing JITAIs for smoking cessation are underway. Given the acceleration of technology in the past decade, combined with the fact that many people

already own wearable devices and that the majority have a smartphone, it makes sense for the health community to take advantage of these types of technology in order to enhance treatment interventions through ambulatory assessment approaches. That said, once empirically-supported interventions are developed, it will be vital to disseminate these to the wider healthcare and consumer community that are focused on smoking cessation. Determining how to make devices user-friendly and affordable will be central to the uptake of these interventions.

In conclusion, ambulatory assessment for smoking cessation has evolved from daily diary studies to wearable wireless sensors. One common theme observed over the past several decades is that through ambulatory assessment, the tobacco field has continually advanced in understanding how to best intervene upon smoking behavior. Currently, the field is moving forward in developing technology to more accurately capture triggers for smoking lapse and smoking behavior, and in utilizing new analytic methodologies (e.g., machine learning) for making sense of the voluminous amount of data that can be created with these technologies. With continued research and advances in technology, wearable wireless sensors have the potential to provide the field with new and exciting information related to smoking behavior and other emerging tobacco products (e.g., e-cigarettes) that can inform theory and treatment. These devices have the potential to allow for the delivery of the right intervention at the right moment in time to impact an individual's ability to stay abstinent from tobacco. However, much of the work on how to make the translation from the assessment data to specific intervention strategies remains to be done. As work continues in this area, the collection of data on participants' response to the technology will be needed in order to inform the development of JITAIs and similar intervention designs. Additionally, the ability to detect good quality data that discriminates between multiple behaviors (e.g., smoking and eating; negative affect and exercise) will also be needed. With the current advancements in technology, the potential to utilize ambulatory assessment to aid smoking cessation is not only exciting, but also necessary to move the field forward in providing the best care possible to individuals wanting to quit smoking.

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Highlights

- Brief overview of EMA for smoking cessation
- Discussion of how lab-based techniques are being used in the real world
- Use of wearable wireless sensors in smoking cessation research
- Detailed discussion of cessation intervention opportunities via wearables
- Challenges and limitations of sensor-based tools in cessation research