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AN ECOLOGICAL MOMENTARY INTERVENTION FOR SMOKING CESSATION: THE ASSOCIATIONS OF JUST-IN-TIME, TAILORED MESSAGES WITH LAPSE RISK FACTORS

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Abstract

Background—Smartphone apps can provide real-time, tailored interventions for smoking cessation. The current study examines the effectiveness of a smartphone-based smoking cessation application that assessed risk for imminent smoking lapse multiple times per day and provided messages tailored to current smoking lapse risk and specific lapse triggers.

Methods—Participants (N=59) recruited from a safety-net hospital smoking cessation clinic completed phone-based ecological momentary assessments (EMAs) 5 times/day for 3 consecutive weeks (1 week pre-quit, 2 weeks post-quit). Risk for smoking lapse was estimated in real-time using a novel weighted lapse risk estimator. With each EMA, participants received messages tailored to current level of risk for imminent smoking lapse and self-reported presence of smoking urge, stress, cigarette availability, and motivation to quit. Generalized linear mixed model analyses

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Contributors

All authors substantively contributed to the development, analysis, and/or writing of the manuscript.

Conflict of Interest

The authors have no conflicts of interest to disclose.

determined whether messages tailored to specific lapse risk factors were associated with greater reductions in these triggers than messages not tailored to specific triggers.

Results—Overall, messages tailored to smoking urge, cigarette availability, or stress corresponded with greater reductions in those triggers than messages that were not tailored to specific triggers (p 's=0.02 to <0.001). Although messages tailored to stress were associated with greater reductions in stress than messages not tailored to stress, the association was non-significant ($p=0.892$) when only moments of high stress were included in the analysis.

Conclusions—Mobile technology can be used to conduct real-time smoking lapse risk assessment and provide tailored treatment content. Findings provide initial evidence that tailored content may impact users' urge to smoke, stress, and cigarette availability.

Introduction

Cigarette smoking remains the leading cause of preventable death, and is responsible for more than 480,000 deaths in the United States and approximately five million deaths worldwide each year (1, 2). Although the majority of smokers want to quit, only a minority are successful (3). Although many available evidence-based smoking cessation treatments exist (e.g., counseling, medications, nicotine replacement therapy)(4); the majority of smokers do not utilize smoking cessation resources (3, 5). Thus, alternative smoking cessation interventions capable of reaching larger proportions of smokers are needed.

In the last decade, an increasing number of smoking cessation interventions have utilized smartphones (e.g., mobile applications, text messaging) to deliver treatment (6, 7). Such interventions are widely available and easily accessible, as 77% of all U.S. adults and 64% of U.S. adults with household incomes less than \$30,000 per year own smartphones (8). Mobile phone-based smoking cessation interventions that incorporate text messaging and quitting advice have been shown to be effective (6, 9). The benefit of technology-based smoking cessation interventions is seen even among socioeconomically disadvantaged groups (10), who typically have comparatively lower cessation rates (11, 12).

Research has highlighted the enormous potential for smartphone applications (apps) to deliver highly innovative, dynamic smoking cessation interventions (13). Aside from their cost-effectiveness and accessibility for diverse populations (14), an additional advantage of smartphone apps is the ability to utilize real-time data collection methods. Ecological momentary assessments (EMAs), collected via smartphone, have enabled researchers to capture thoughts, affect, and behavior in real-time within natural settings (15–17).

Furthermore, EMAs enable the examination of moment-to-moment changes that may influence an individual's likelihood of smoking lapse. EMA research has identified several factors associated with smoking lapse, including urge to smoke (18, 19), proximity to others smoking (20), proximity to tobacco retail outlets (21, 22), and stress (16, 23). The majority of antecedents to smoking lapse have been shown to be environmental or situational, and lapses often occur shortly after exposure to smoking cues (17, 18, 24). The consistent pattern of behaviors and cues preceding smoking episodes has enabled the use of predictive algorithms (17) and machine learning (25) to identify moments of high risk for smoking

lapse among individuals trying to quit. For example, Businelle et al. (2016) (17) developed a weighted lapse risk algorithm that correctly identified 80% of all first lapses based on the presence of six risk factors in the 4-hour period preceeding the lapse. Thus, smartphone-delivered, just-in-time interventions may be ideally suited to detect moments of lapse risk and intervene to reduce risk among those trying to quit.(13)

One tactic used in many successful health interventions is message tailoring (26), in which message content is matched to an individual's behavioral, psychosocial, and/or demographic factors (27). A meta-analysis of the impact of tailored messages on health behaviors revealed that messages tailored to the participant's personal psychosocial factors (e.g., self-efficacy, motivation) were significantly more effective in changing health behaviors than those without tailoring (26). Existing mobile-based smoking cessation interventions have used strategies such as text messaging (6) or user-triggered content (e.g., opening an app to access cessation advice or calling a helpline) (13) rather than just-in-time, adaptive tailoring of content. A content analysis of 225 Android-based smoking cessation apps revealed that tailoring was used sparingly and was often very simple (28). For example, 90% of evaluated smoking cessation apps were passive and did not include messaging or notifications to encourage users to interact with the app (28). However, tailoring and proactive attempts of an app to engage users is associated with higher numbers of app downloads and higher user ratings (28). Although users prefer highly interactive, tailored smoking cessation apps, to our knowledge, very few have utilized tailored messaging in real-time.

The present study examined the utility of a smoking cessation app that assessed risk for imminent smoking lapse multiple times per day and provided tailored treatment content based upon current level of smoking lapse risk and lapse triggers. The primary objective of this study was to determine whether receiving intervention messages tailored to specific lapse triggers in real-time (i.e., urge to smoke, stress, and easily available cigarettes) would be associated with greater reductions in self-reported smoking urge, stress, and cigarette availability than messages not tailored to those specific lapse triggers.

Methods

Participants and Procedure

Participants were recruited from a safety-net hospital smoking cessation program that provides an educational session with a respiratory therapist, weekly group support sessions, and weekly individual visits with a physician or prescribing provider for cessation medication (including nicotine replacement therapy, varenicline, and bupropion). Individuals were eligible to participate if they: 1) earned a score ≥ 4 on the Rapid Estimate of Adult Literacy in Medicine (REALM) (29) indicating ≥ 6 th grade English literacy level, 2) were willing to quit smoking 7 days after their first clinic visit, 3) were ≥ 18 years of age, 4) had an expired CO level ≥ 8 ppm suggestive of current smoking, 5) were currently smoking ≥ 5 cigarettes per day, and 6) were willing and able to attend 7 assessment sessions.

The study procedure was approved by the Institutional Review Boards at the University of Texas Southwestern Medical Center and the University of Texas School of Public Health. Data collection took place between June 2014 and August 2015. Participants were followed

weekly from 1 week pre-quit through 4 weeks post-quit, with one follow-up visit 12-weeks post-quit. At baseline, all participants were provided with a Samsung Galaxy Light smartphone preloaded with the Smart-Treatment (Smart-T) app, and were asked to carry it at all times for 3 weeks (1 week pre-quit and 2 weeks post-quit). The Smart-T app has been described in detail elsewhere (30). Briefly, Smart-T is a multi-component adjunctive smoking cessation app featuring 1) a “Quit Tips” button offering cessation advice, coping strategies, and quitting benefits, 2) a “Medications” button offering information about smoking cessation medications, 3) a “Phone a Counselor” button that calls the free Texas Smoking Quit Line, and 4) an algorithm that evaluates current risk of smoking lapse based on EMA responses and pushes risk-tailored messages to help participants cope with lapse triggers and thereby reduce the likelihood of smoking lapse. Intervention messages were delivered at the completion of every EMA.

Participants completed EMAs 5 times a day for three consecutive weeks (1 week pre-quit, 2 weeks post-quit), including 1 daily diary (delivered 30 minutes after waking) and 4 random assessments. In addition, participants could self-initiate EMAs when they had an urge to smoke or when they lapsed. Participants were compensated with gift cards (\$40–\$120) based on the percentage of random and daily diary assessments completed over the study period, with a minimum requirement of 50% assessments completed to receive any payment. Given the purpose of the current study, only post-quit EMAs were included in the analyses.

Measures

At baseline, all participants answered demographic questions including age, sex, race/ethnicity. Participants also answered questions about their smoking history, including the Heaviness of Smoking Index (HSI) to assess their nicotine dependence. The HSI is a 2-item measure commonly used to assess nicotine dependence (31). Scores range from 0 to 6 and scores ≥ 4 indicate moderate to high dependence. On the quit date, participants were asked if they smoked “even a puff” since 10:00 p.m. on the night prior to their quit date visit. At each in-person visit following the scheduled quit date, participants were asked if they smoked “even a puff” during the past 7 days. Abstinence was verified via expired carbon monoxide (CO) at each visit using a Vitalograph CO monitor. Self-reported abstinence over the specified time period and a CO reading below 8 ppm (10 ppm on the quit date) were required to be considered abstinent.

During each EMA, participants answered questions about psychological, social, and environmental factors including stress, urge to smoke, cigarette availability, motivation to quit, recent alcohol consumption, and interaction with someone smoking. Participants were asked to rate on a scale from 1 (strongly disagree) to 5 (strongly agree) if they had an urge to smoke, if they felt stressed, how easily available cigarettes were to them [1 (not at all) to 5 (easily available)], their motivation to avoid smoking [1 (strongly agree) to 5 (strongly disagree)], whether they were interacting with anyone who was smoking (yes/no), and whether they drank alcohol in the last hour (yes/no).

Lapse Algorithm and Tailored Messages

Risk of smoking lapse was estimated in real-time using a weighted lapse risk estimation formula developed by Businelle et al. (2016) (17). The formula included six variables shown to be associated with lapse, including urge to smoke, stress, recent alcohol consumption, interaction with someone smoking, motivation to quit, and cigarette availability. These lapse risk factors were weighted based upon their ability to discriminate moments of high lapse risk from moments of low risk for lapse (described in detail in Businelle et al., 2016) (17).

During the two-week post-quit period, participants received automated, individually tailored messages based upon their current level of risk for imminent smoking lapse and self-reported presence (agreeing or strongly agreeing) of four of the six lapse triggers (Figure 1). Level 0 messages were pushed when a participant indicated that they lapsed and were no longer interested in quitting smoking. These messages highlighted the benefits of quitting and focused on improving motivation for cessation. Level 1 messages were pushed when responses indicated a low level of imminent lapse risk, and focused on general cessation advice. Level 2 messages were delivered when responses indicated high risk for imminent smoking lapse. Level 2 messages were also delivered when the participant smoked earlier that day or the day before, or the participant indicated on their first daily assessment that they had a greater than 25% chance of smoking that day. Level 2 messages suggested ways to cope with current lapse risk factors and were tailored to the participant's highest rated of four current lapse triggers: stress, smoking urge, easy access to cigarettes, and low motivation to quit. When multiple triggers were equally highly rated, one message was delivered with preference given to negative affect/stress, smoking urge, cigarette availability, and motivation to quit, respectively. Examples of each message type are listed in Table 1.

Data Analysis

Descriptive statistics were generated to describe participant demographic characteristics and the frequencies of automated EMA message types. To determine if messages tailored to specific EMA reported lapse triggers were followed by greater reductions in those triggers compared with messages not tailored to those triggers, we defined the primary outcome variable as the change in lapse risk trigger (i.e., stress, urge, and cigarette availability), which was the difference between a participant's risk factor score at the time of receiving a message and their risk score at the next random assessment within the same day. Participant-initiated assessments (i.e., urge and lapse EMAs) were excluded from these analyses. Very few cessation motivation messages were delivered ($n = 11$); therefore, analyses for this risk factor were not conducted.

To account for correlated observations within participants, generalized linear mixed models with restricted maximum likelihood estimation were used to determine if messages tailored to specific lapse risk factors reduced these triggers more than messages that were not tailored to these specific triggers. The main fixed effect in each model was a dichotomous variable that indicated if a participant received a tailored message for the outcome variable of interest. All models included a random effect for subject, using a scaled identity matrix covariance structure. Each model also included fixed effects to account for day in the study, age, race, gender, education level, heaviness of smoking index at baseline, and lapse risk

score. Because higher risk factor scores had the potential for greater reductions compared to low risk factor scores (e.g., a stress rating of 5 could decrease by 4, but a stress rating of 3 could only decrease by 2), we conducted additional analyses to address the potential for regression to the mean. Specifically, models were restricted to those assessments in which the risk factor of interest was high (e.g., when participants reported that they strongly agree (5) or agree (4) that they had an urge to smoke; Model 2), and both the risk factor of interest and overall risk level were high (Model 3).

Results

Participants

Participants (N=59) in the analytic sample were primarily female (54.2%), African American (51.4%), and were on average 52.0 years old (SD = 7.0). Most participants (67.2%) had a total combined family income of less than \$16,000 per year. At baseline, participants smoked an average of 20.9 cigarettes (SD=12.9) per day, had been smoking for an average of 31.8 (SD=10.7) years, and had an average HSI score of 3.54.

EMA and Automated Messages

Participants completed 4,355 post-quit EMAs during the study period. Of these, 689 were participant-initiated, 843 were daily diary assessments, and 2,823 were random. Among the post-quit daily and random EMAs, 217 (6.0%) were followed by level 0 messages (already lapsed and did not wish to continue with the quit attempt), 1,649 (45.7%) were followed by level 1 messages (low level of lapse risk), and 1,742 (48.3%) were followed by level 2 messages (high level of lapse risk). Of the tailored level 2 messages, 536 (30.8%) targeted stress, 300 (17.2%) targeted urge, 895 (51.4%) targeted cigarette availability, and 11 (0.6%) targeted motivation to quit.

Association of Tailored Messages with Reduction in Lapse Risk Factors

Intervention messages focused on coping with smoking urges corresponded to significantly greater reductions in urges, as measured at the next EMA compared with messages that were not tailored to smoking urge (i.e., level 0 and level 1 messages, and level 2 messages that targeted stress or cigarette availability; Table 2, Model 1, $p < 0.001$). Results remained significant when the model was restricted to EMAs wherein smoking urge was endorsed (Model 2, $p < .001$), and among EMAs wherein smoking urge was endorsed and overall lapse risk was high (Model 3, $p < .001$).

Stress-focused messages corresponded to significantly greater reductions in self-reported stress at the next EMA compared with messages that were not tailored to stress (i.e., level 0 and level 1 messages, and level 2 messages targeting urge or cigarette availability; Table 3, Model 1, $p < 0.001$). Results were no longer significant after restricting the model to those observations where stress was endorsed ($p = 0.892$) (Model 2); however, tailored stress messages were associated with greater reductions in stress compared to messages not tailored to stress when restricting to those assessments where stress was endorsed and overall lapse risk was high (Model 3, $p = 0.020$).

Finally, messages tailored to reduce easy access to cigarettes corresponded to greater reductions in self-reported cigarette availability compared with messages not specifically tailored to reduce easy access to cigarettes (i.e., level 0 and level 1 messages, and level 2 messages that targeted urge or stress; Table 4, Model 1, $p < 0.001$). The effect remained significant when restricting to only those EMAs wherein cigarette availability was high (Model 2, $p < .001$), and when restricting to those EMAs wherein both cigarette availability and overall lapse risk were high (Model 3, $p < .001$).

Discussion

This study examined whether messages tailored to specific lapse risk factors (i.e., urge to smoke, stress, cigarette availability) were more effective than messages that were not tailored. We found that messages tailored to smoking urge and cigarette availability corresponded to greater reductions in smoking urge and cigarette availability compared with messages that were not tailored to those specific triggers in all 3 models. Overall, tailored messages aimed to reduce urge to smoke and cigarette availability were associated with greater reductions in those risk factors, even when restricting to situations that were deemed high risk. These findings replicate and extend previous work indicating that tailored intervention content may perform better than non-tailored messages for achieving desired health related outcomes (26, 32). The current study provides preliminary evidence that messages that are tailored to address smoking lapse triggers in real-time, as they are experienced, may be clinically useful in attenuating factors that have been shown to contribute to relapse.

Several factors that may have contributed to the greater reductions in risk factors associated with the tailored urge and cigarette availability messages warrant further discussion. In this study, messages were tailored to a specific lapse risk factor that was reported by the participant seconds earlier, making the messages especially relevant. The relevance of the message may have increased the likelihood that users would read, understand, pay attention to, and be persuaded by the messages (33, 34). Similarly, the tailored messages were designed to provide immediate support to users, thereby offering treatment information and help immediately in the moment of need, rather than only at scheduled clinic visits.

Although messages tailored to self-reported stress were associated with greater reductions in stress than messages not tailored to stress, the association was non-significant ($p=0.892$) when only moments of high stress were included in the analysis. Yet, the model was significant when the sample was limited to moments where both lapse risk and stress were high (i.e., analyses comparing tailored stress messages to tailored urge and cigarette availability messages, $p = 0.020$). There may be several explanations for this finding. First, in situations where participants reported equally high ratings for urge, stress, and cigarette availability, stress was given the highest priority to receive the tailored message. In fact, of the 536 EMAs in which stress messages were delivered, participants also reported high urges to smoke in 40.1% of these EMAs, and participants reported easy access to cigarettes in 58.4% of these EMAs. In contrast, when urge messages were delivered, only 12.2% of participants also reported high stress. Thus, when tailored stress messages were delivered, more lapse risk factors could be present compared with situations in which urge or cigarette

availability messages were delivered. Second, stress may be less modifiable and more nuanced compared to smoking urges (in which chewing a piece of nicotine gum could ease symptoms) (35) or cigarette availability (in which disposing of or moving away from accessible cigarettes could reduce their availability). Overall, future work is needed to explore the nature and complexity of tailored messaging for stress-related triggers in the context of smoking.

The current study provides novel evidence that smartphone apps can be used to assess risk for imminent smoking lapse and automatically deliver tailored smoking cessation advice. Public health practitioners could use this type of just-in-time-adaptive-intervention (36) for a variety of populations that are motivated, but do not have the means or desire to receive in-person support and/or advice for health behavior change. Second, the current findings indicate the possibility that message tailoring for health behaviors may be helpful in real time. Practitioners should continue to implement tailoring for effective health outcomes, especially relating to reduction in urge and cigarette availability.

This study has several limitations. First, the sample was small and socioeconomically disadvantaged, and participants were paid to complete the EMAs used to trigger treatment messages. Thus, it is unclear if results would generalize to other populations of unpaid smokers seeking cessation help. Second, an EMA-only control group was not included; nor was the messaging strategy randomly assigned in the moment (i.e., tailored vs. untailored). Although current findings are promising, it remains unclear whether the messages were causally associated with reductions in specific risk factors. Future research will randomize people or situations to messaging types to evaluate causality.

Third, the reduction in risk factor scores following the receipt of risk-tailored intervention messages may be due to regression to the mean. For example, smoking urges ebb and flow and rarely stay extremely high over long periods. We attempted to address this issue by restricting the analyses to those observations in which the risk factor of interest was high (Model 2), and when overall lapse risk was high (Model 3). This allowed us to determine if self-reported risk factors that triggered a tailored message were associated with greater reductions in risk than self-reported risk factors that did not trigger a tailored message (e.g., high urges only triggered tailored urge messages when the risk for lapse was high and participants reported that current urge levels were higher than stress). However, these analyses cannot substitute for a randomized control trial that assigns smokers to intervention groups, or randomly assigns risk-tailored messages vs. untailored messages in comparable situations.

Overall, the present study is the among the first to assess risk for imminent smoking lapse and use a smartphone app to deliver tailored treatment messages based on smoking risk factors reported in real-time. Results illustrate that mobile technology can be used to conduct real-time risk assessment and subsequently provide tailored treatment content. Furthermore, findings provide initial evidence that tailored content may reduce users' urges to smoke and cigarette availability. This innovative intervention could be modified and used with other populations of smokers, and the just-in-time approach may be applied to other modifiable health risk factors.

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Highlights

- Smartphones can be used to assess risk for smoking lapse in real-time.
- Smartphone apps can deliver just-in-time adaptive interventions to prevent lapse.
- Tailored messages may reduce users' urges to smoke and cigarette availability.

*If trigger ratings were tied, priority was given in this order: stress, urge, cigarette availability, motivation.

Figure 1.
Smart-T Message Logic

Table 1

Example Messages

Message Level	Themes	Example Messages
Level 0	Benefits of quitting, general motivation, planning for quit attempt	<ul style="list-style-type: none"> • On average, non-smokers live 12 years longer than smokers AND ex-smokers live up to 10 years longer than smokers who don't quit. • Identify your smoking triggers. For example, coffee or meals trigger some people to smoke. Avoiding your triggers will help you stay quit during your first post-quit week.
Level 1	General cessation advice, maintaining abstinence	<ul style="list-style-type: none"> • Remember: Every day without cigarettes is a success. The first few hours and days are the hardest. It gets easier as time goes by. HANG IN THERE! You're doing it! • Friends and family can help you stay quit. Call on them when you are having an urge! Asking for help is a strength not a weakness!
Level 2	Tailored to highest risk factor (e.g., urge, stress, cigarette availability)	<ul style="list-style-type: none"> • Have you tried this? Some people find that sucking on mints or chewing gum helps them get through cravings. • Don't let negative emotions keep you from a healthier life! When you feel stressed or angry, distract yourself, go for a walk, get out of the situation for a few minutes, try deep breathing exercises. • Avoid being around cigarettes or people smoking. Don't make the temptation worse by staying in situations that are too tempting.

Table 2
Fixed Effects from Mixed Model Predicting Change in Urge Score After Receipt of an Urge Message

	Model 1 ^a		Model 2 ^b		Model 3 ^c	
	β (SE)	p	β (SE)	p	β (SE)	p
Urge Message vs. All Others	−0.620 (0.064)	< 0.001	−0.227 (0.066)	0.001	−0.295 (0.071)	< 0.001
Intercept	−0.208 (0.233)	0.376	−1.65 (0.995)	0.104	−1.63 (1.112)	0.151

Note. All models were adjusted for day in study, age, race, gender, education level, heaviness of smoking index at baseline, and lapse risk score at message receipt.

^aModel includes all assessments (Level 0, 1, and 2 EMAs)

^bModel restricted to assessments where participants endorsed the presence of an urge (Level 0, 1, and 2 EMAs when urge score = 4)

^cModel restricted to assessments where participants endorsed the presence of an urge, and risk for lapse was high (Level 2 EMAs when urge score = 4)

Fixed Effects from Mixed Model Predicting Change in Stress Score After Receipt of a Stress Message

Table 3

	Model 1 ^a		Model 2 ^b		Model 3 ^c	
	β (SE)	p	β (SE)	p	β (SE)	p
Stress Message vs. All Others	−0.311 (0.044)	< 0.001	−0.027 (0.073)	0.715	−0.25 (0.108)	0.021
Intercept	0.079 (0.169)	0.642	−1.343 (1.248)	0.289	−0.959 (1.082)	0.382

Note. All models were adjusted for day in study, age, race, gender, education level, heaviness of smoking index at baseline, and lapse risk score at message receipt.

^aModel includes all assessments (Level 0, 1, and 2 EMAs)

^bModel restricted to assessments where participants endorsed the presence of stress (Level 0, 1, and 2 EMAs when stress score = 4)

^cModel restricted to assessments where participants endorsed the presence of stress, and risk for lapse was high (Level 2 EMAs when stress score = 4)

Table 4
Fixed Effects from Mixed Model Predicting Change in Cigarette Availability Score After Receipt of a Cigarette Availability Message

	Model 1 ^a		Model 2 ^b		Model 3 ^c	
	β (SE)	p	β (SE)	p	β (SE)	p
Cigarette Availability Message vs. All Others	-0.212 (0.038)	< 0.001	-0.115 (0.034)	0.001	-0.232 (0.043)	< 0.001
Intercept	-0.31 (0.675)	0.647	-0.579 (0.724)	0.428	-0.361 (0.615)	0.560

All models were adjusted for day in study, age, race, gender, education level, heaviness of smoking index at baseline, and lapse risk score at message receipt.

^aModel includes all assessments (Level 0, 1, and 2 EMAs)

^bModel restricted to assessments where participants endorsed the presence of easily available cigarettes (Level 0, 1, and 2 EMAs when cigarette availability score = 4)

^cModel restricted to assessments where participants endorsed the presence of easily available cigarettes and risk for lapse was high (Level 2 EMAs when cigarette availability score = 4)