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Brief report
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Brief report

Effect of Real-Time Monitoring and Notification of Smoking Episodes on Smoking Reduction: A Pilot Study of a Novel Smoking Cessation App

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Abstract

Introduction: Smartphone applications (apps) for smoking cessation are becoming increasingly available, but their efficacy remains to be demonstrated. We conducted a pilot study of SmokeBeat, a novel app designed for use with smartwatches and wristbands. SmokeBeat is powered by a data analytics software platform that processes information from the sensors embedded in wearables. It relies on an original algorithm to identify in real time the hand-to-mouth gestures that characterize smoking a cigarette. We examined whether merely monitoring and notifying smokers on smoking episodes in real time via the SmokeBeat app would lead to reduction in smoking.
Methods: Forty smokers (9 women and 31 men) who expressed a wish to reduce or quit smoking were randomly assigned to using the SmokeBeat app for 30 days or to a wait-list control group. All participants completed questionnaires at baseline and at the end of the study, including their level of smoking. Smokers in the experimental condition were notified whenever the SmokeBeat system detected a smoking episode and were asked to confirm or deny it.
Results: The SmokeBeat algorithm correctly detected over 80% of the smoking episodes and produced very few false alarms. According to both self-report and detection of smoking episodes by the SmokeBeat system, smokers in the experimental condition showed a significant decline in smoking rate over the 30-day trial ($p < .001$). There was no change in the smoking rate of the control group.
Conclusion: These preliminary results suggest that automatic monitoring of smoking episodes and alerting the smoker in real time may facilitate smoking reduction in motivated smokers.
Implications: Raising the awareness of smokers to the act of smoking in real time, as the SmokeBeat app is able to do, can counter the automaticity of the smoking habit. Bringing smoking under conscious awareness may benefit smokers who are motivated to reduce or quit smoking to gain better control of their smoking behavior and reduce cigarette intake.

The immense societal toll associated with cigarette smoking in terms of illness, mortality, and financial costs makes the reduction of smoking rates at a population level a primary worldwide objective. A recent addition to this effort has been smartphone applications ("apps") providing psychological interventions to aid smoking cessation. Smartphone apps have important advantages that potentially can make them a major player in the efforts to reduce smoking globally. In contrast to individual or group therapy for smoking cessation, smartphone apps are available around the clock to an estimated 2.3 billion smartphone owners around the world (https://www.statista.com/statistics/330695/number-of-smartphone-users-worldwide/) and are free or very inexpensive to use. And because people carry their smartphones wherever they go, these apps are available to the smoker whenever he or she wishes to use them.

While there are presently more than 400 smoking cessation apps in the market, however, we could find only a couple whose efficacy has been tested.[1,2] Moreover, reviews of existing smoking cessation apps recently noted that so far, these apps have not exploited their unique potential advantages.[3,4]

This pilot study examines a novel app for smoking cessation, which is the first such app designed for use with wearables (smartwatches and wristbands). Using information from the sensors embedded in wearables, the SmokeBeat app relies on an original algorithm to identify the hand-to-mouth gestures that characterize smoking a cigarette and alert smokers in real time about smoking episodes. Specifically, raw data are collected from the accelerometer and gyroscope sensors, and following data stabilization and noise filtering, the SmokeBeat algorithm determines which specific hand-to-mouth movements being performed by the wearable user signify smoking. Thanks to its ability to detect smoking in real time, SmokeBeat does not depend on users registering every smoking event, as do all other current apps. This unique feature has the potential to increase smokers' awareness of his or her smoking behavior, countering the tendency of the smoking habit to become automatic and "mindless".[5] Indeed, self-monitoring was recently shown to be a critical behavior change technique in smoking cessation interventions.[6] We therefore expected that notifying smokers in real-time of smoking episodes would increase awareness and may lead to smoking reduction in smokers wishing to reduce or quit smoking.

Method

Participants

Forty-two participants were recruited using advertisements in Facebook inviting people aged 18–45 who smoked at least five cigarettes per day and who wished to reduce or quit smoking. Participants had to own an android smartphone version 4.3 or higher, which was required for running the version of SmokeBeat used in this study. They were offered a fixed payment of 1000 New Israeli Shekels (equivalent to approximately $250) in return for participating in the study for the full 30 days. Participants were assigned in alternating order to either the experimental group or a wait-list control group, as described below. Two participants dropped out of the study, both from the experimental group and both very early on, so the final number of participants was 40 (9 women and 31 men, all Caucasian). The study was conducted in the Tel Aviv Area and was approved by the Ethical Board of Tel Aviv University.

Materials

The SmokeBeat app is part of Somatix, a behavioral modification software platform designed to develop interventions based on data gathered from real-time detection of hand-to-mouth gestures using standard wearables (smartbands and smartwatches). In the case of SmokeBeat, the Somatix platform uses machine-learning algorithms to detect smoking episodes and notify detection back to the user in real time. In the present study, participants were asked following every detection of a smoking episode several questions in regard to the episode. Participants were asked about their position during this episode (sitting, standing, lying down, walking, driving), whether the elbow of their smoking hand was leaning on something, whether they were eating or drinking, whether they felt stressed before smoking the present cigarette, and the extent to which they enjoyed the cigarette (rated from "extremely" to "not at all").

Baseline data were collected before the first use of the app via web-based questionnaires. These included demographics (sex, age, and education) and information regarding the subjects' smoking history and smoking habits, including the Fagerström Test of Cigarette Dependence (FTCD[7,8]). At the end of the study, participants in the experimental group responded to questions via the smartphone that were designed to evaluate their experience of using the app (see details in Supplementary Material).

Procedure

Participants who responded to our ad (via email) received a document that explained the experimental process. If they were interested in participating, they were asked to sign an informed consent form and were assigned in alternating order to the experimental or the control group. Participants in the experimental group received a smartwatch (LG Urbane or LG G-R) and were instructed to wear it on the hand that they used for smoking (four participants wore the watch on their right hand, and the remaining 16 on their left hand). They then downloaded the SmokeBeat app to their smartphone and completed the baseline questionnaire over the web. Those assigned to the wait-list control condition did not receive a watch and only completed the web-based baseline questionnaire. In the next 14 days, participants in experimental group received pop-up notifications whenever the system detected a smoking episode. The notification appeared on both the watch and the phone and remained until the user confirmed or denied smoking (overall, 93% of the notifications were responded to and 90% of the participants answered more than 80% of the notifications). A response to the notification opened the app and presented the cigarette follow-up questions described above. If a participant smoked and the episode was not detected by the app, he or she was instructed to report having smoked through the app in real time using the designated icon and then answer the cigarette follow-up questions. In addition, participants could actively search in the app for statistical information regarding their smoking patterns (see Supplementary Material for details), but this information was never pushed to the users. After 14 days, the development team manually tuned the detection algorithm to fit each subject's specific smoking patterns (as a result of the tuning, the rate of false positives dropped from 6.19% to 2.84%) and the subject continued using the app in the same way for 16 more days. We used the second period to assess the precision of the smoking detection process and the full 30 days to evaluate the effect of smoking monitoring and detection on smoking patterns. At the end of the 30 days period participants in the experimental condition returned the watch (all of them did), and all participants completed the end-of-study questionnaire and were then thanked and payed for their participation.

Statistical Analysis

Analyses of data were conducted with the IBM SPSS 24 package. We used a mixed-model ANOVA to analyze the self-reported CPD at baseline and end of study in the two groups. Changes in CPD in the experimental group over time (as detected by the app) were assessed using repeated measures ANOVA. Statistical significance was set at .05 and η^2 was used as an estimate of effect size. Correlations were estimated using Pearson correlation coefficients.

Results

Table 1 displays the baseline data of participants in our study. The two groups did not differ in age, education level, and the age of smoking initiation. However, despite the random assignment, the control group reported smoking more cigarettes per day and had higher scores on the FTCD.

There was a main effect of group on self-reported CPD, $F(1, 38) = 19.24$, $p < .001$, reflecting the baseline differences noted above between the two groups. There was also an effect of time, so that overall participants smoked less at the end of the study compared to baseline, $F(1, 38) = 7.99$, $p < .001$. However, an identical interaction effect between group and time, $F(1, 38) = 7.99$, $p < .001$, indicates that the decline was solely due to the experimental group (Figure 1). Whereas the control group reported identical number of CPD at baseline and at end of study (both $M = 18.75$), the experimental group reported a significant decline in the same 30-day period ($M_{\text{baseline}} = 12.00$, $M_{\text{end-of study}} = 9.25$), $F(1, 38) = 15.98$, $p < .001$, $\eta^2 = .296$.

In the next step of the analysis, we examined the information received from the SmokeBeat platform in regard to detection of smoking episodes. Participants reported having smoked 64.23% of their cigarettes while sitting and 18.09% while standing, and the detection rates for these positions were 87.29% and 89.67%, respectively, with overall detection rate (across all positions) of 82.29%. False alarms—cases where the system erroneously detected and reported a smoking episode—occurred only at 2.85% of the total episodes reported by the system. The results of the analysis of change in CPD in the experimental group as assessed by the SmokeBeat algorithm were consistent with those self-reported by the participants, $F(29, 551) = 2.542$, $p < .001$, $\eta^2 = .118$. A negative linear contrast on these data was significant, $t(28) = 2.77$, $p = .0122$, confirming the decline in cigarettes detected and reported through the SmokeBeat app over the 30-day study (Figure 1). The correlation between self-reported and observed change in CPD was moderate but significant, $r = .45$, $p = .049$.

Because the groups differed at baseline in CPD and FTCD scores, we sought to rule out the possibility that the differences between the groups at the end of the study could be explained by the higher dependence level of participants in the control group. This was done by examining the correlations between change in CPD and baseline FTCD scores in each group. In both groups, the reported decline in CPD was positively correlated with FTCD scores, though the correlation was significant only in the experimental group ($r = .51$, $p = .022$) and not in the control group ($r = .12$, $p = .61$), very likely because of the low variance in CPD change over time in the latter group. Notably, in the experimental group, FTCD scores were also correlated with the decline in CPD as detected by the SmokeBeat algorithm ($r = .58$, $p = .007$).

Discussion

The results of this pilot study of SmokeBeat are encouraging in two respects. First, the smoking detection algorithm of the app was able to detect over 80% of smoking episodes in "real life" conditions with negligible frequency of "false alarms." Second, the study provides preliminary evidence that automatic monitoring of smoking episodes and notifying the smoker in real time when smoking episodes are detected can lead to smoking reduction.

We hasten to emphasize that this study has several limitations and that the findings raise several issues that should be resolved. First, the control group smoked more and was more dependent than the experimental group, which represents a failure of randomization which we cannot account for. However, higher baseline CPD and dependence was associated with more, rather than less smoking reduction, so the group difference at baseline cannot serve as an alternative explanation to our findings. Second, as seen in Figure 1, there was a gap between the CPD figures self-reported by the experimental group at the beginning and end of the study (upper part, approximately 12 CPD at the beginning and 9.5 CPD at the end of the study) and the ones derived from the app, which include cigarettes missed by the algorithm and reported by the smoker via the app (approximately 9.5 CPD at the beginning and 5 CPD at the end of the study). We do not know if this gap represents an overestimation of the CPD figure by the smokers or under-detection by the app, and future studies will help to determine that. At any rate, the reported reduction in CPD was very similar to that detected by the app (approximately 2.5 CPD), which suggests that the reduction in CPD in the experimental group is a reliable finding. Third, our control condition differed from the experimental condition in several respects, which limits our ability to conclude which of those were critical for our findings (eg, we cannot assess the effects of merely wearing the smartwatch). Fourth, the current version of the app cold not provide us information on the extent to which users actively searched for statistical information about their smoking rates, so we cannot assess any effects that this information may have had on changes in CPD. Fifth, we have no data on any long-term effects of using the SmokeBeat app, which remains to be examined future studies with the SmokeBeat app. And sixth, our participants were recruited using Facebook ads and were mostly men, which may limit the generalizability of our results.

Finally, we should note that the unique ability of SmokeBeat to identify smoking behavior in real time can be used to generate data analytics on a vast number of smoking parameters and to distill from these data both general and personal smoking patterns. The detection algorithm also makes it possible to deliver incentives and coping strategies at the moment that they are most relevant to the smoker and to provide feedback on goal progress in real time, without depending on the smoker's fluctuating state of energy,

Table 1. Baseline Data (Means with SD in Parentheses) of Participants in the Study ($N = 20$ in Each Group)

	Group			
	Experimental	Control	*t*	*p*
Age	25.90 (4.22)	29.55 (8.72)	−1.684	.100
Years of education	12.45 (1.23)	13.10 (2.00)	−1.238	.223
Age started smoking	16.95 (2.98)	16.60 (2.37)	0.411	.683
Reported cigarettes per day	12.00 (2.90)	18.75 (7.92)	−3.576	.00097
FTCD score	12.50 (3.32)	19.95 (8.56)	−3.631	.00083

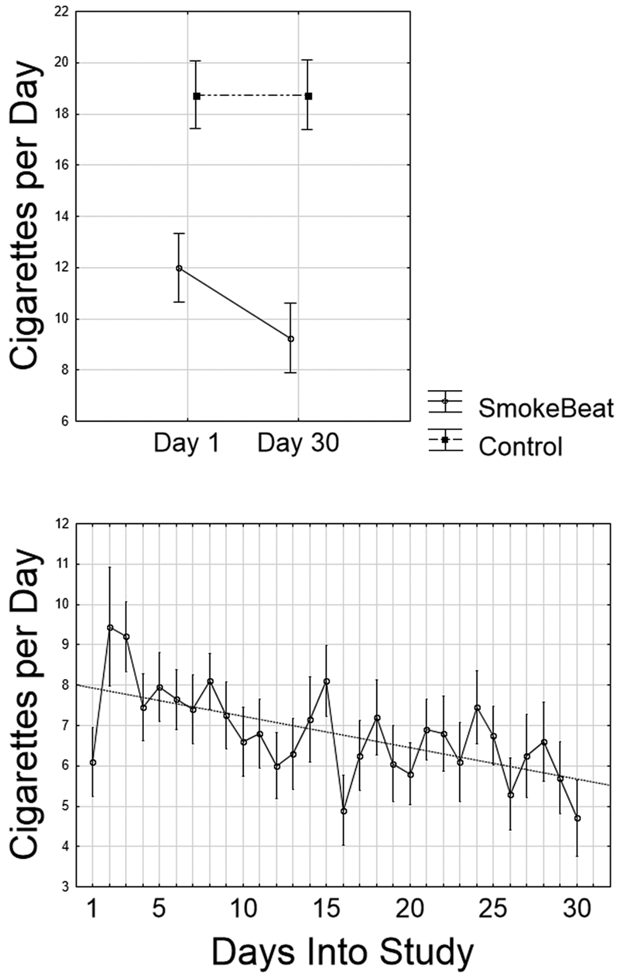

Figure 1. Above, cigarettes per day in the two group at baseline and end of study. Below, cigarettes per day in the experimental group across the 30 days of the study. Bars represent standard errors. The straight line in the bottom figure represents the linear regression fit. (Note that the detection data for day 1 are partial, as this was the first day in which smokers used the app).

motivation, or awareness. We believe that these unique advantages of the SmokeBeat system have the potential to enrich the research on smoking behavior and improve the efficacy and dissemination of effective treatment for smoking cessation, especially considering the projected growth in the prevalence of wearables over the next few years (http://www.ccsinsight.com/press/company-news/2332-wearables-market-to-be-worth-25-billion-by-2019-reveals-ccs-insight).

Supplementary Material

Supplementary data are available at *Nicotine and Tobacco Research* online.

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Declaration of Interests

RD serves on the Advisory Board of Somatix. The author declares that he had full access to all of the data in the study and that he takes responsibility for the integrity of the data and the accuracy of the data analysis.

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