Original Research

Predictors of Utilization of a Novel Smoking Cessation Smartphone App

Emily Y. Zeng,[1,2] Roger Vilardaga, PhD,[2,3]
Jaimee L. Heffner, PhD,[2] Kristin E. Mull, MS,[2]
AU1 *and Jonathan B. Bricker, PhD[1,2]*

Departments of [1]Psychology and [3]Psychiatry and Behavioral Sciences, University of Washington, Seattle, Washington.
[2]Division of Public Health Sciences, Fred Hutchinson Cancer Research Center, Seattle, Washington.

Abstract

Background: *Understanding the characteristics of high and low utilizers of smartphone applications (apps) for smoking cessation would inform development of more engaging and effective apps, yet no studies to date have addressed this critical question. Informed by prior research on predictors of cessation Web site utilization, this study examines the degree to which baseline demographic factors (gender, age, and education), smoking-related factors (smoking level and friends' smoking), and psychological factors (depression and anxiety) are predictive of utilization of a smartphone app for smoking cessation called SmartQuit.* **Materials and Methods:** *Data came from 98 participants randomized to SmartQuit as part of a pilot trial from March to May 2013. We used negative binomial count regressions to examine the relationship between user characteristics and utilization of the app over an 8-week treatment period.* **Results:** *Lower education (risk ratio [RR] = 0.492; p = 0.021), heavier smoking (RR = 0.613; p = 0.033), and depression (RR = 0.958; p = 0.017) prospectively predicted lower app utilization. Women (RR = 0.320; p = 0.022), those with lower education (RR = 0.490; p = 0.013), and heavier smokers (RR = 0.420; p = 0.039) had lower utilization of app features known to predict smoking cessation.* **Conclusions:** *Many of the predictors of utilization of smoking cessation apps are the same as those of cessation Web sites. App-delivered smoking cessation treatment effectiveness could be enhanced by focusing on increasing engagement of women, those with lower education, heavy smokers, and those with current depressive symptoms.*

Key words: *mobile health, smoking cessation, utilization, tobacco, nicotine, applications, smartphone*

Introduction

E-health, the application of electronics and other technologies to health, is a growing field supporting data-driven implementation of technology to deliver evidence-based health interventions in areas such as mental health,[1] physical activity,[2] and chronic disease.[3] E-health has been widely used to target tobacco use at the national and state levels through smoking cessation Web sites, quitlines, and text message–based interventions.[4,5] Given that tobacco use remains the number one cause of preventable deaths in the United States[6] and funding for population-level smoking cessation programs (e.g., quitlines) remains below the recommended Centers for Disease Control and Prevention levels,[7] it is important now more than ever to develop e-health technologies that are effective and low cost and have high population reach.

Mobile health (m-health) technologies are a rapidly expanding portion of the e-health landscape. Among m-health interventions, smartphone-based smoking cessation software applications (apps) have a broad population reach. There are over 400 smoking cessation apps available for public download[8] and a total of 3.2 million downloads in the United States in 2012–2013 alone.[9,10]

Despite the rapid growth of apps for smoking cessation and their potential value to reach a large population, the high attrition rates observed in other m-health apps[11,12] suggest that low utilization could potentially limit the effectiveness of smoking cessation apps, as well. In general, discontinuation of smartphone app use is a problem; 26% of app users download an app only to discontinue after one use, and 74% of app users typically discontinue by the 10th use.[13] Understanding user characteristics that are linked to less active engagement with smoking cessation apps—particularly with the apps' key treatment components—would inform design modifications to address the problem of lack of utilization. However, the degree to which individual characteristics predict smoking cessation app utilization has, to our knowledge, never been studied before.[14]

We developed a smoking cessation app called SmartQuit that combines principles of evidence-based tobacco treatment from the U.S. Clinical Practice Guidelines[15] with novel exercises based on Acceptance and Commitment Therapy (ACT).[16] ACT is a behavioral therapy that has been used to treat psychological conditions like anxiety and depressive disorders[17,18] and has a broader applicability to other types of health behaviors like smoking cessation.[19] In our pilot randomized controlled trial, 196 participants were randomized into either SmartQuit or QuitGuide (an app based on Smokefree.gov, the most accessed smoking cessation Web site in the world).[20] The acceptability and smoking cessation rates of the apps were assessed 2 months after randomization via a follow-up survey. Our results indicated that, on average, SmartQuit was used more often, led to higher overall satisfaction, and had higher 30-day point prevalence cessation outcomes at the 2-month follow-up, albeit not significant.[20] As with most interventions for smoking cessation, utilization predicted cessation: there was a trend indicating that people who opened SmartQuit more times were more likely to quit smoking.[20] Similar results of higher utilization predicting cessation were found in a randomized controlled trial of a smoking cessation app for young adults.[21] Additionally, in a recent process analysis study examining utilization of SmartQuit features, we found that the features in SmartQuit that were most predictive of smoking cessation at the 2-month follow-up[22] were (1) Tracked Practice of ACT Skills, (2) Tracked Practice of Letting Urges Pass, and (3) Viewed Quit Plan Overview. AU2

Even though SmartQuit has shown promise as a smoking cessation app and we have demonstrated that greater overall use of the app as well as several specific features are associated with a better treatment outcome, how much these specific user characteristics might have influenced their utilization is unknown. Prior research on smoking cessation Web sites, a technological predecessor of smoking cessation apps with a more mature empirical literature, suggests several possible demographic predictors of utilization. Specifically, eight studies of Web-delivered interventions found that the following user characteristics were predictive of higher utilization: (1) being female,[23–28] (2) being older,[23,27–29] (3) having a higher education,[28,29] (4) being a moderate versus heavy or light smoker,[30] and (5) having fewer smoking friends.[28] In addition to demographic characteristics, psychological factors such as depression[31–33] and anxiety[31,33,34] may negatively impact utilization because these are risk factors for low adherence to other types of behavioral interventions.

The goal of this study was to examine the degree to which previously identified demographic factors (gender, age, education, level of smoking, friends who smoke) and psychological factors (depression and anxiety) are predictive of (a) overall SmartQuit use and (b) use of specific SmartQuit features predictive of cessation (i.e., Tracked Practice of ACT Skills, Tracked Practice of Letting Urges Pass, and Viewed Quit Plan). The results of this study could further inform treatment development efforts to increase the utilization and effectiveness of smartphone apps for smoking cessation and provide guidance in tailoring smartphone interventions for specific segments of the smoking population.

Materials and Methods

PARTICIPANTS

For this *post hoc* analysis using data from our pilot trial, participants included only the 98 adult smokers assigned to the SmartQuit arm. We did not include QuitGuide in this analysis because it only has self-reported measures on utilization, which are less objective than SmartQuit's automatically recorded utilization data. Inclusion criteria were as follows: (1) 18 years of age or older, (2) smoked at least 5 cigarettes daily for the past 12 months or longer, (3) wanted to quit smoking in the next 30 days, (4) had access to an iPhone® (Apple, Cupertino, CA) 4, 4S, or 5 smartphone, (5) was willing and able to read in English, (6) was not participating in other smoking cessation interventions, and (7) had never used the Quit Guide smartphone app. *Table 1* gives descriptive characteristics of the study sample. T1

Table 1. Baseline Characteristics of SmartQuit Trial Participants Randomized to the Acceptance and Commitment Therapy Arm

DEMOGRAPHICS	VALUE
Age (years)	41.5 (12.0)
Male	46 (47%)
High school or less education	14 (14%)
Smoking behavior	
Light smoking (5–10 cigarettes per day)	29 (30%)
Heavier smoking (11 or more cigarettes per day)	69 (70%)
Friend and partner smoking	
Living with partner who smokes	24 (24%)
Close friends who smoke	1.7 (1.5)
Current mental health symptoms	
CES-D (n=94)	9.2 (6.0)
GAD-7 (n=97)	7.2 (5.7)

Data are mean (standard deviation) values or number (%) as indicated (n=98 unless noted).

CES-D, Center for Epidemiologic Studies Depression Scale (cutoff for clinically significant depression is ≥10); GAD-7, Generalized Anxiety Disorder (cutoff for clinically significant anxiety is ≥10).

RECRUITMENT

Following our prior successful approach to recruitment via Web-based as well as traditional media channels,[35] participants were recruited from March to May 2013 using Facebook ads, Google ads, and a press release by the Fred Hutchinson Cancer Research Center Communications Department. Participants were sent a link to the study's recruitment page where they were instructed to complete the online screening survey. We excluded multiple log-ins from the same Internet protocol address. A total of 738 people completed the online screening survey, of whom 400 were eligible for the study, and 340 provided consent online. Of those who consented, 205 completed the baseline survey and verified their interest in the study via a confirmation phone call. Afterward, these participants were e-mailed a link to enroll in the study, and the 196 participants who clicked on the link were randomized into the trial (98 per arm).

APP

Participants randomized into SmartQuit were given an access code that they used to activate the app after downloading it from the iTunes® (Apple) app store. SmartQuit content was adapted from our Web- and telephone-based ACT interventions, which showed promising smoking cessation results.[36,37] The app includes exercises designed to increase willingness to experience trigger situations without smoking, increase recovery skills for smoking lapses, and develop self-compassion. A more detailed description of SmartQuit can be found elsewhere.[38] In addition, SmartQuit offers three features that were shown to predict smoking cessation outcomes: Tracking Practice of ACT Skills, Tracking Practice of Letting Urges Pass, and
T2 Viewing the Quit Plan[22] (*Table 2*).

Table 2. Descriptions of SmartQuit App Features

SMARTQUIT FEATURE	DESCRIPTION
Tracked Practice of ACT skills	ACT feature: Users record how many times they practiced ACT skills. The skills include three exercises covering motivation to quit, eight for handling cravings, and four for recovering from a slip.
Tracked Letting Urges Pass	ACT feature: Users track how many times in a day they were able to let an urge to smoke pass without acting on it.
Viewed Quit Plan Overview	USCPG feature: Users view their personalized quit plan, which includes what inspires them to quit, their chosen quit date, how many cigarettes they plan to cut back per day, financial cost of their smoking, use of pharmaceutical aids, and a list of support people.

ACT, Acceptance and Commitment Therapy; USCPG, U.S. Clinical Practice Guidelines.

MEASUREMENTS

Baseline predictors. Our baseline survey contained measures of anxiety and depression as well as the demographic variables that predicted smoking cessation Web site utilization in prior studies: gender,[17,23–27] age,[23,26–28] education,[27,28] smoking level,[30] and number of friends who smoked[28]:

- *Education.* Education level was dichotomized into high school or less education versus post–high school education.
- *Heavier smoking.* Smoking level was measured by asking participants how many cigarettes per day they typically smoked in the past 30 days. They chose from six categories: 1 cigarette, 2–4 cigarettes, 5–10 cigarettes, 11–20 cigarettes, 21–30 cigarettes, or more than 30 cigarettes. Based on the median of participants' responses to this item (11–20 cigarettes per day), we dichotomized this variable and characterized heavier smoking as individuals who smoked at least 11 cigarettes per day. Positive scores on this variable indicated heavier smoking.
- *Number of close friends who smoked.* We measured number of close friends who smoked by asking participants "Of your five closest friends, how many of them smoke cigarettes regularly?"
- *Anxiety.* Anxiety was assessed using the Generalized Anxiety Disorder Scale (GAD-7), a brief seven-item survey used to screen for generalized anxiety disorders in the general population. This scale has excellent internal consistency, test–retest reliability, and construct validity.[39] The scale contains symptoms of GAD based on *Diagnostic and Statistical Manual of Mental Disorders, 4th Edition, Text Revision* criteria and asks participants to rank how much each symptom has bothered them over the past 2 weeks from "Not at all = 0" to "Nearly every day = 3." Scores range from 0 to 21, which are calculated by summing up responses to all of the items. Higher scores indicate higher levels of anxiety. In this analysis, the Cronbach's alpha for the GAD-7 was 0.93.
- *Depression.* Depression was measured with the 10-item Center for Epidemiologic Studies Depression Scale (CES-D). The scale contains answer choices ranging from "Rarely or none of the time = 0" to "Most or all of the time = 3" in response to questions about the frequency of depressive symptoms experienced in the past week. Scores range from 0 to 30 and are calculated by summing item responses. Previous studies have shown that the CES-D has adequate construct, criterion-based, and content validity[40] as well as test–retest reliability and internal consistency.[41] A higher score indicates higher levels of depression. In this analysis, the Cronbach's alpha for the CES-D was 0.86.

SmartQuit app utilization. We measured app utilization as the number of times a participant opened the app over the 8 weeks of treatment. Feature utilization was measured as the number of times participants opened each SmartQuit feature predictive of smoking cessation: Tracked Practice of ACT Skills, Tracked Practice of Letting Urges Pass, and Viewed the Quit Plan.[22] During the study, participants were given an access code that linked their utilization pattern data with the baseline information they provided. Only participants with an access code could access the app. Although Internet connection was not required for the app to function, it was required to deliver participant utilization data to the app developer's secured server. The app stored up to 70 event analytics and delivered the information once the user opened the app and had network available. This procedure for collection and reporting of utilization data was evaluated during beta testing to identify missing events, and the process was repeated until no missing events were detected. Event reporting was also monitored during the course of the trial to ensure that events were being tracked as expected.

STATISTICAL ANALYSIS

As typically observed in count outcomes,[42] histograms of the number of SmartQuit and specific features openings suggested a negative binomial distribution. Therefore, we fit negative binomial count regressions to estimate risk ratios (RRs) for utilization of the app. RRs are interpreted as the multiplicative effect of a particular characteristic (e.g., lower education) on utilization of the app by participants. Due to the exploratory nature of this analysis and the small sample size, each independent demographic variable (gender, age, education, smoking level, and number of friends who smoke) was evaluated in a separate model, with number of times logged in as the outcome variable. Similar models were run with each of the psychological variables (anxiety and depression). Statistical significance and trends were set at $\alpha = 0.05$ and $\alpha = 0.10$, at AU3
respectively. Visual inspection and analyses were done using version 3.0.1 of R[43] and the MASS[44] and ggplot2[45] packages.

Results

The median number of app openings was 11, and the median length of app use (from the date of initial use to the date

Table 3. Baseline Predictors of SmartQuit Openings and Features Utilization

	FEMALE GENDER	AGE	HIGH SCHOOL OR LESS EDUCATION	AT LEAST 11 CIGARETTES/DAY	NUMBER OF FRIENDS WHO SMOKE	GAD-7	CES-D
SmartQuit openings							
RR	0.940	1.00	0.490	0.610	0.990	0.980	0.960
95% CI	0.62, 1.44	0.98, 1.02	0.28, 0.94	0.39, 0.95	0.84, 1.17	0.94, 1.02	0.93, 0.99
p value	0.790	0.977	0.021[a]	0.033[a]	0.862	0.206	0.017[a]
Tracked Practice of ACT Skills							
RR	0.320	0.990	0.450	0.470	0.820	1.01	0.970
95% CI	0.12, 0.86	0.94, 1.04	0.13, 2.54	0.14, 1.30	0.53, 1.28	0.92, 1.11	0.89, 1.06
p value	0.022[a]	0.539	0.272	0.165	0.249	0.863	0.467
Tracked Letting Urges Pass							
RR	0.620	1.02	0.530	0.420	0.950	0.970	0.950
95% CI	0.28, 1.34	0.98, 1.06	0.19, 1.90	0.17, 0.93	0.68, 1.36	0.91, 1.05	0.89, 1.02
p value	0.220	0.220	0.256	0.039[a]	0.728	0.403	0.120
Viewed Quit Plan Overview							
RR	0.970	0.990	0.490	0.790	1.09	1.00	0.970
95% CI	0.66, 1.43	0.98, 1.01	0.29, 0.88	0.52, 1.20	0.95, 1.26	0.96, 1.03	0.94, 1.01
p value	0.871	0.424	0.013[a]	0.278	0.194	0.776	0.119

[a] $p < 0.05$. AU10

ACT, Acceptance and Commitment Therapy; CES-D, Center for Epidemiologic Studies Depression Scale; GAD-7, Generalized Anxiety Disorder; RR, risk ratio.

of final use) was 28 days. Descriptive data on specific feature utilization are contained in another publication.[22] As shown T3 in *Table 3*, heavier smoking, depression, and lower education were predictive of fewer SmartQuit openings. Participants who smoked 11 or more cigarettes per day at baseline opened the SmartQuit app 39% less often than those who smoked 10 or fewer cigarettes (RR = 0.610; p = 0.033). For every 1-point increase in the baseline CES-D depression scale, there was a 4% decrease in SmartQuit utilization (RR = 0.960; p = 0.017). Lower education (high school or less) was associated with a 51% decrease in the number of SmartQuit app openings (RR = 0.490; p = 0.021).

We also examined utilization of specific SmartQuit features that were previously identified as key "active ingredients."[22] Women used the Tracked Practice of ACT Skills feature in SmartQuit 68% fewer times than men did (RR = 0.320; p = 0.022). Participants with a lower education (high school or less) used the Viewed the Quit Plan feature 51% fewer times than those with higher education (RR = 0.490; p = 0.013). Finally, heavier smokers used Tracked Letting Urges Pass 58% less than lighter smokers (RR = 0.420; p = 0.039).

Discussion

The goal of this study was to explore baseline characteristics predictive of utilization of a smoking cessation app in order to empirically inform future treatment development efforts. Results indicated that lower education and heavier smoking were strongly associated with, and depression was mildly associated with, lower overall app utilization. None of the other demographic or smoking-related characteristics previously observed to predict smoking cessation Web site utilization (being female,[24–29] age,[24,28–30] and number of friends who smoke[29]) or anxiety,[31,33,34] which predicts worse adherence to other behavioral interventions, were predictive of SmartQuit openings. In terms of specific feature use, being female, lower education, and heavier smoking strongly predicted lower utilization of key SmartQuit features predictive of cessation.[22]

Considering the small body of studies on user characteristics that predict smoking cessation Web site utilization, this study found mixed support for previous findings. Similar to prior studies on predictors of Web site utilization,[28–30] we found that lower education and heavier smoking were both associated with lower app utilization. This is problematic because low education[46,47] and heavy smoking[48,49] are also associated with lower rates of smoking cessation. Our results did not replicate other predictors (being female, being older, and having fewer smoking friends) of smoking cessation Web site utilization. Perhaps the predictors of smoking cessation Web site utilization are different from the predictors of smoking cessation app utilization. Future research should test that possibility.

We also looked at two psychological factors that have not been examined in prior studies as predictors of utilization: anxiety and depression. Depression was significantly, albeit mildly, predictive of a lower number of app openings, suggesting that current depression may serve as a motivational barrier to app utilization.[50]

Our findings suggest that the very same groups that are most likely to use smoking cessation apps (e.g., women and people with lower educational attainment[51]) are the users who have the lowest engagement with them. Results of this study can address this paradox and point to a need for methods to better engage smokers who are female, with lower levels of education and higher levels of depression and smoking. Given that previous findings indicate tailored health messages based on individual characteristics result in better outcomes than traditional strategies,[52] tailoring app content on characteristics of low utilizers (e.g., pushing tips for handling depression to users who report depressive symptoms) may increase utilization.

In addition to making the content more personally relevant to specific user groups, the effectiveness of strategies to direct them toward the key intervention components of the app before they discontinue use should also be evaluated. For example, prompting and reinforcement—two critical yet underused elements of persuasive technology design[53]—are possible methods of increasing utilization of specific features associated with quitting.

Because barriers to engagement in smoking cessation apps are consistent with barriers of engagement in face-to-face smoking cessation interventions (heavier smoking,[54] higher depression,[54,55] lower education,[56] and being female[54]), smoking cessation apps can also incorporate previously proven strategies for improving engagement in face-to-face smoking cessation interventions, such as contingency management.[57–59]

A final possible strategy for increasing utilization among high-risk users is the addition of features to make social support available through the app, either from other users or from a professional. Adding social support to e-health interventions has been found to increase utilization by as much as 50%.[60] The value of testing such methods for increasing the usage of these features is underscored by the fact that, once these high-risk subgroups actually use the features, they are several times more likely to quit smoking.[22]

LIMITATIONS

A key limitation of this study is that our findings are predictive associations. The sample size did not allow multivariate testing of models to determine the extent of shared variance among predictors. Additionally, we could not determine the amount of time participants spent on the SmartQuit app or on each specific feature of the app. For example, it is possible that a user who opened the app five times could have spent less time on the app in total than a user who opened the app for one lengthy period of time. However, reliably tracking the amount of time a user spends on the app is difficult because most smartphones have multitasking features that allow users to run multiple apps at once. Finally, results may not be generalizable to all smoking cessation apps. Larger studies are needed to examine the replicability of our findings.

Conclusions

This was the first analysis of the predictive relationship between baseline user characteristics and utilization of a smoking cessation app. Accordingly, this study takes a critical first step toward addressing the ubiquitous problem of low utilization, which results in less exposure to critical intervention content. By designing apps that address utilization barriers such as low education, depression, and heavy smoking, developers can take full advantage of the capability of smartphone apps to reach and effectively treat millions of smokers.

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Disclosure Statement

No competing financial interests exist.

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Address correspondence to:
Jonathan B. Bricker, PhD
Division of Public Health Sciences
Fred Hutchinson Cancer Research Center
1100 Fairview Avenue North, M3-B232
P.O. Box 19024
Seattle, WA 98109

E-mail: jbricker@fredhutch.org

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AU1 Affiliations renumbered in author order. Provide academic degree for Zeng (BA? BS?).
AU2 Mention of Table 2 deleted here. If left in then Tables 2 and 1 require renumbering in text citation order.
AU3 Unable to copy symbol exactly so alpha symbol used. Provide correction as needed.
AU4 Give last accessed date (month, day, year).
AU5 Give last accessed date (month, day, year).
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AU10 Only ** used in original so * deleted.