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How Smart are Smartphone Apps for Smoking Cessation? A Content Analysis

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Abstract

Introduction: Smartphone technology is ideally suited to provide tailored smoking cessation support, yet it is unclear to what extent currently existing smartphone "apps" use tailoring, and if tailoring is related to app popularity and user-rated quality.

Methods: We conducted a content analysis of Android smoking cessation apps (n = 225), downloaded between October 1, 2013 to May 31, 2014. We recorded app popularity (>10 000 downloads) and user-rated quality (number of stars) from Google Play, and coded the existence of tailoring features in the apps within the context of using the 5As ("ask," "advise," "assess," "assist," and "arrange follow-up"), as recommended by national clinical practice guidelines.

Results: Apps largely provided simplistic tools (eg, calculators, trackers), and used tailoring sparingly: on average, apps addressed 2.1 ± 0.9 of the 5As and used tailoring for 0.7 ± 0.9 of the 5As. Tailoring was positively related to app popularity and user-rated quality: apps that used two-way interactions (odds ratio [*OR*] = 5.56 [2.45–12.62]), proactive alerts (*OR* = 3.80 [1.54–9.38]), responsiveness to quit status (*OR* = 5.28 [2.18–12.79]), addressed more of the 5As (*OR* = 1.53 [1.10–2.14]), used tailoring for more As (*OR* = 1.67 [1.21–2.30]), and/or used more ways of tailoring 5As content (*OR* = 1.35 [1.13–1.62]) were more likely to be frequently downloaded. Higher star ratings were associated with a higher number of 5As addressed (b = 0.16 [0.03–0.30]), a higher number of 5As with any level of tailoring (b = 0.14 [0.01–0.27]), and a higher number of ways of tailoring 5As content (b = 0.08 [0.002–0.15]).

Conclusions: Publically available smartphone smoking cessation apps are not particularly "smart": they commonly fall short of providing tailored feedback, despite users' preference for these features.

Introduction

Current evidence has demonstrated the usefulness of mobile technology in supporting smoking cessation.[1] The most recent Cochrane review, based on 20 studies and a total sample size of 9100 smokers, indicated significant benefit of mobile phone-based smoking cessation interventions on long-term outcomes, with a relative risk estimate of 1.71, compared to no intervention or less intensive intervention via mobile.[1] These effects were achieved with fully-automated, highly cost-effective programs of unprecedented reach. They were also achieved with a relatively low level of technological sophistication, as up to this point, mobile technology approaches to smoking cessation have largely used text messaging.[2–6]

Smartphones "apps"[7] offer more sophisticated tools for interacting with participants, including intuitive user interfaces and greater functionality. Whether apps are effective in supporting smoking cessation remains unclear, as randomized controlled trials are still needed to assess their effectiveness, though preliminary work suggests their usefulness.[8,9] Also unclear is the degree to which currently existing smoking cessation apps use their capacity for sophisticated functionality. At present, simplicity appears to be the most sought-after feature of mobile interventions. A recent randomized trial comparing a texting versus app intervention for smoking cessation in young adult smokers (n = 102) found that texting was more successful in moving smokers to abstinence (58% vs. 30% abstinent at 6-week follow-up), which the authors explained may be due to the fact that texting is simple and well-known.[10] In line with this desire for simplicity, currently existing smoking cessation apps appear to be largely simplistic. Content analyses of smoking cessation smartphone apps have shown that they intervene on smoking primarily by providing relatively simple tools: calculators to track money saved and health benefits accrued (31.9%), calendars to track days until or since the quit attempt (27.7%), trackers to ration or limit cigarette use (10.6%), and hypnosis sessions for smoking cessation (6.4%).[11] Apps also rarely adhere to established clinical practice guidelines for smoking cessation.[11,12]

The focus on simplicity is perhaps unfortunate, because one of the great advantages of mobile interventions, apart from their unprecedented reach, is their immense capacity for tailoring, that is, their ability to provide health behavior messages individualized to unique persons.[13] Tailoring is defined as a "means [of] creating communications in which information about a given individual is used to determine what specific content he or she will receive, the contexts or frames surrounding the content, by whom it will be presented and even through which channels it will be delivered".[14] It is a concept that has a long-standing history in health communications research, where it has originally guided the development of health-related print materials[15] and communications in primary care settings,[16] and more recently has been used to enhance health messaging for older adult smokers[17] and smokers with a low readiness to quit.[18]

Health communications[19] and neuroscience[20] research both have demonstrated that tailoring health behavior intervention materials increases the effectiveness of health messages. In health communications research, a meta-analysis of 57 health behavior change interventions, spanning a combined sample size of n = 58 454 participants, showed that tailoring was associated with more positive health behavior outcomes.[19] Importantly, the benefit of tailoring was found for both relatively simple tailored intervention messages (eg, on demographics) as well as more sophisticated ones (eg, tailoring feedback based on theoretical constructs related to the health behavior change). Meanwhile, in neuroscience, a functional magnetic resonance imaging study examining n = 91 smokers receiving neutral (ie, not related to smoking cessation), untailored, and tailored smoking cessation messages found that increases in activation in the dorsomedial prefrontal cortex, a self-related processing region of the brain, to tailored messages predicted quitting during a 4-month follow-up.[20] These findings illustrate that tailoring makes a difference in improving health behaviors, both on a macro (eg, public-health) and a micro (eg, neuro-biological) level. Mobile technology is ideally suited to provide such tailored health behavior messages, given the ability of mobile devices to interact with users dynamically.[21]

The degree to which existing smoking cessation apps leverage technology to provide tailored feedback is unclear. Moreover, it is unclear whether users prefer simpler or more sophisticated smoking cessation apps. Thus, we conducted a content analysis of currently available smoking cessation apps. The goal of this study was to examine the level of tailoring present in these apps, and to test if the use of tailoring mattered in terms of the app's popularity and user-rated quality. As a guiding framework, we rated these features within the context of the national clinical practice guidelines for smoking cessation, where we specifically focused on the absence versus presence of using the 5As ("ask," "advise," "assess," "assist," and "arrange follow-up")[22] to promote smoking cessation (ie, assess smoking status, advise to quit smoking, assess the readiness to quit smoking, assist in a quit attempt, and arrange follow-up).

Methods

Sample

This content analysis focused on Android smoking cessation apps, as smartphones using the Android operating system currently hold the largest market share in the United States and worldwide.[23] Note also that content-wise, smoking cessation apps for Android and iOS (the operating system used by the iPhone family) are largely similar, with lower cost and higher user ratings of Android apps being the only identified differences between smoking cessation apps for Android and iOS.[12] Smoking cessation apps were downloaded between October 1, 2013 and May 31, 2014 from Google Play using the search terms "smoking," "smoking cessation," "quit," "stop smoking," and "quit smoking." Pro-smoking apps[24] were not downloaded. Of the downloaded apps (n = 273), n = 48 were excluded from analysis, because they either were no longer available online by the time the second rater completed the app coding (73%), did not function properly (19%), were not in English (4%) or were advertisements for other apps (4%). The remaining n = 225 apps were included in the analyses. A full listing of included apps is provided in the online Supplementary Materials. Each app's number of downloads and user rating (if available) were recorded from Google Play as measures of app popularity, in line with previous research,[12] and user-perceived quality, respectively. User ratings were provided on a 5-point scale, with 1 being the lowest rating and 5 the highest.

Coding of Apps

The content of the apps was rated by two independent raters using a predefined rating form (see the online Supplementary Material for the rating form). Three overall domains were rated per app: (1) basic descriptors, using the categories and indices used by Abroms et al.,[11] (2) tailoring in the general approach taken by the apps, and (3) tailoring in addressing the 5As, as recommended in the US Clinical Practice Guideline for Treating Tobacco Use and Dependence.[25] Categories were refined as unanticipated features were encountered. Inter-rater reliability was "good"[26] for coding indices of tailoring in the general approach taken by the app (average κ = 0.78), and "very good"[26] for coding the presence of the 5As (average κ = 0.81) and their specific subcategories (average κ = 0.86). Discrepancies (ie, a feature was found to be "present" by one rater, but "absent" by the other) occurred in 2.3%, 3.6%, and 2.1% of the apps on average across the variables rated for general approach, 5As, and subcategories of the 5As, respectively. These discrepancies were resolved by consensus rating of at least two raters (not necessarily the same two who rated the app originally), after discussing general rules for resolving discrepancies in a larger group (four research staff members). Raters took approximately 15–45 minutes to initially test and rate each app. Thereafter, apps stayed installed on the smartphone used on a daily basis by research staff, and ratings were updated as new, time-triggered features were encountered during the next 6–12 months.

Analytic Strategy

We calculated means with standard deviations and total *n* with percentages for the coded variables. In order to identify qualities of the apps which were associated with the popularity and user-rated quality of the apps, we used univariate regression models. Given the descriptive nature of this content analysis, we used an explorative approach, and thus did not correct *P* values for multiple testing. We used logistic regression to test predictors of popularity (ie, >10 000 downloads vs. fewer, the top 20% of the rated apps), and linear regression to test predictors of user-rated quality (ie, average number of stars per app). Analyses concerning the quality of the apps were restricted to the apps that had star ratings (77% of the apps). As predictors, we used summary variables from all three rated domains, as described in their respective tables (Tables 1–3).

Results

Basic Descriptors and Types of App

The rated smoking cessation apps varied widely on numerous basic dimensions (Table 1). Several apps were only downloaded a handful of times (eg, 1–10 times, 16%), but some apps (20%) were quite popular (ie, >10 000 downloads). Most apps were freely available (70%), free of nuisance factors (eg, only 35% included advertisements; 34% contained grammatical errors), and apps generally received positive ratings (ie, on average, 3.9 ± 0.9 stars out of 5). The vast majority of apps (98%) targeted smokers, but apps for social supporters of smokers (3%) or nontargeted informational apps (1%) also existed.

The examined apps offered a variety of tools to support smoking cessation, with many apps (44%) offering multiple tools. The most common tool was a calculator (41%) to track money saved, health benefits accrued, or lifespan lost due to smoking. Calendar functions (36%), which tracked days until or following a quit attempt, or tracked nonsmoking days were also common. Less common were other types of trackers (18%), which helped ration or limit cigarette use or tracked urges and contextual factors related to smoking, and hypnosis apps (21%). Other types of apps (10%) offered distractors from urges to smoke (eg, games, audio clips, modifiable pictures of lungs), motivational quotes and messages to encourage quitting smoking, or used scare tactics (eg, showing aversive pictures of the negative health outcomes of smoking).

Tailoring in the General Approach Taken by the Apps

Apps can tailor their interactions with users in their general approach to interactions. We coded three such ways: (1) by being interactive, where the input provided by the user would result in specific feedback; (2) by being proactive, where the app reaches out to users after initial use; and (3) by being responsive to the quit attempt, where the functionality of the app changes after the quit day. Our results indicate that tailoring in these general approaches was limited (Table 2).

The most commonly used general tailoring approach was two-way interactions (45% of apps). For the most part, this type of two-way interaction was fairly simple (eg, tracking health benefits, number of cigarettes). More sophisticated ways in which to utilize two-way interactions were more limited. Only 4% of the apps asked for and responded to different types of information at different times during the quit process, and only 3% of apps “remembered” previously provided information in a later interaction.

Table 1. Basic Descriptors of the Rated Apps (*n* = 225)

Descriptor	% of apps (*n*)	Mean (*SD*)
Basic facts		
Number of downloads		
1–10	15.6 (35)	
10–100	13.3 (30)	
100–1000	25.3 (57)	
1000–10 000	26.2 (59)	
>10 000	19.6 (44)	
Price		
Free	69.8 (157)	
If price, $ to download		$3.30 (3.3)
Nuisance factors		
Displays advertisements	35.1 (79)	
Contains grammatical mistakes	34.2 (77)	
Average file size (in MB)		6.6 (12.0)
Guidance to navigate app		
Included tutorial at download	9.3 (21)	
Had help functions	24.4 (55)	
Quality ratings		
App has been rated	76.9 (173)	
If rated, average number of stars (out of 5)		3.9 (0.9)
Average number of stars based on 10+ raters		3.9 (0.6)
Apps with written reviews	58.7 (132)	
If reviewed, average number of reviews per app		32.1 (97.7)
Content of app		
Who is the app intended for?[a]		
Smoker	98.2 (221)	
Social support for smoker (eg, friend, spouse, healthcare provider)	2.7 (6)	
Nontargeted information	0.9 (2)	
Type (44% of apps do multiple things)		
Calculator: to track money saved or health benefits accrued	41.8 (94)	
Calendar: to track days until or since the quit attempt	36.0 (81)	
Tracker: to help ration/limit cigarette use to specific times or certain number of cigarettes	18.2 (41)	
Hypnosis	21.3 (48)	
Other	9.8 (22)	

[a]Multiple targets were possible.

Other general tailoring approaches were less frequent. Most apps took a passive stance (90%), where the app did not reach out to users to interact with it. When proactive alerts were used by an app (10%), multiple types of alerts were typically used (9% of apps). Very few apps were responsive to the users’ quit attempts. Only 11% changed their functionality after the quit date. For the most part, such changes were minimal, for example, starting or restarting the tracking of statistics (eg, days stayed abstinent) or offering congratulations on milestone achievements. Very few apps adapted to the postquit status of the user in more comprehensive ways (2%), for example, by using new graphics and unlocking new content to differentiate app content between preparing to quit versus managing withdrawal.

Table 2. Prevalence of Tailoring in Terms of the General Approach Taken by the Apps

Approach	*n*	%
Interactive		
Two-way: user input is used to provide tailored feedback	101	44.9
Dynamic two-way: user is asked for different information at different times	10	4.4
Remembering and dynamic two-way: user information provided at an earlier interaction is used in a later interaction	6	2.7
Proactive: app reminds user to interact with it	23	10.2
Auditory alert	1	0.4
Visual alert	1	0.4
Both as well as vibrate and other options for alerts	21	9.3
Responsive to quit attempt (ie, app content changed postquit)		
At all	24	10.7
More than minimally	5	2.2

Using Tailoring in Addressing the 5As

In examining the extent to which the apps implemented the 5As (Table 3), we found that the apps generally addressed "assist" (96%), but less frequently addressed the other four As. A substantial proportion of apps assessed smoking status in one way or another ("ask": 51%), and offered direct advice to quit smoking ("advise": 47%), but very few apps "assessed" (8%) the users' readiness to change and interest in quitting, and only a few apps "arranged follow-up" (11%).

In terms of "ask," apps most commonly asked about the number of cigarettes smoked per day (49%), or the cost of cigarettes (35%). Apps rarely (2%–6%) asked about smoking information that could be used to tailor feedback (eg, smoking motivations, smoking triggers). Consequently, the "advise" portion of the apps was largely generic, and only personalized very rarely (1%). Similarly, for "assess," few apps assessed readiness to change (8%), and fewer still offered an opportunity to indicate a lack of readiness (6%), and or followed-up by addressing barriers to quitting (<1%).

Adherence to "assist" most commonly consisted of providing basic information (43%; eg, e-books providing facts about the risks of smoking), relatively generic messages (eg, reminders about money saved [36%], tracking the cigarettes not smoked [32%]) or simple activities (eg, distractions from urges [28%]). More specific information, such as links to external smoking cessation resources (11%) or details about pharmaceutical options (18%), were less commonly provided, and more specific calls to action, such as providing opportunities to interact with other users for mutual support (8%), or direct referrals to quitlines or support groups (5%) were rare. Unique opportunities of smartphone technology to support the quit attempt by, for example, playing back personalized messages (4%) or reminding smokers of personalized motivations to quit smoking (2%), were rarely utilized. Indeed, even one of the most basic levels of tailoring, the act of scheduling a quit day, was an option in only 33% of the apps, and, of those, very few built on this information by providing support for that quit attempt (9%).

Finally, "arranging follow-up," or in the case of an app, actually providing follow-up care, was a rare feature in the reviewed apps. Very seldom did an app check-in with users about their quit attempt, either before (4%) or after (7%) the quit attempt, and very few apps provided support in the case of relapse by encouraging app users to set a new quit day (4%) or by reminding them that quitting takes practice (3%).

In summary, on average, apps addressed 2.1 ± 0.9 of the 5As (range: 1 [24%]–5 [3%]) and used any type of tailoring (as indicated by the ✓ in Table 3) for 0.7 ± 0.9 of the 5As. Of the 14 identified ways in which tailoring was done for the 5As, apps used on average 0.9 ± 1.6 tailoring features.

App Qualities Related to Popularity and User-Rated Quality

Results of the univariate logistic regression analyses (Table 4) showed that app qualities from all three coded domains (ie, basic descriptors, general approach, adherence to 5As) were related to the popularity of the rated apps. In terms of basic qualities, apps that were free of charge (odds ratio [*OR*] = 12.05 [2.83–51.40]) and free of nuisance factors (*OR* = 2.24 [1.14–4.41]) were more likely to be downloaded frequently (>10 000). Tailoring in the general approach the app used to interact with users was also related to popularity, where apps that used two-way interactions (*OR* = 5.56 [2.45–12.62]), proactive alerts (*OR* = 3.80 [1.54–9.38]), and responsiveness to prequit versus postquit status (*OR* = 5.28 [2.18–12.79]) were more likely to be frequently downloaded. Finally, apps that addressed the 5As, and did so in a tailored manner, were more likely to be frequently downloaded: apps that addressed more of the 5As rather than fewer (*OR* = 1.53 [1.10–2.14]), used tailoring for more As rather than fewer As (*OR* = 1.67 [1.21–2.30]), and/or used more ways of tailoring 5As content rather than fewer (*OR* = 1.35 [1.13–1.62]) were more likely to be frequently downloaded.

Fewer app qualities were related to the user-rated quality of the app (Table 4), though it should be noted that the statistical power to detect significance was also lower, given that only a subset of apps (77%) had user-rated quality ratings. Specifically, higher star ratings were associated with better adherence to the 5As, where a higher number of 5As addressed (b = 0.16 [0.03–0.30]), a higher number of 5As with any level of tailoring (b = 0.14 [0.01–0.27]), and a higher number of ways of tailoring 5As content (b = 0.08 [0.002–0.15]) were all related to higher star ratings.

Discussion

This content analysis of Android smoking cessation apps (n = 225) extends the current knowledgebase on publically available smoking cessation apps[11,12] by providing an update in a rapidly innovating environment on how well existing apps adhere to best practices for smoking cessation, as exemplified by the utilization of the 5As. Previous content analyses examined apps existing on June 24, 2009[11] and February 11, 2012,[12] respectively. This content analysis examined apps existing between October 1, 2013 and May 31, 2014. Additionally, unlike other recent content analyses of smoking cessation apps,[12,27] which focused on the most popular[12] or a random subset[27] of available apps, this content analysis took a comprehensive approach, and evaluated every existing smoking cessation Android app. Finally, and most importantly, unlike previous content analyses, the purpose of this content analysis was to evaluate to what degree existing smartphone apps are "smart," that is, utilize the sophisticated technology underlying apps to provide tailored health messages. We found that adherence to best practices continues to be low,

Table 3. Prevalence of Tailoring With Respect to Adherence to National Smoking Cessation Clinical Guidelines

5 As (✓ indicates tailoring)	*n*	%
Ask (app assessed smoking status)	114	50.7
Current smoking		
Number of cigarettes smoked per day	111	49.3
Time until first cigarette of the day	12	5.3
Smoke when sick	3	1.3
✓ Reasons to smoke/quit smoking	8	3.6
Smoking triggers		
✓ Time of day smoking triggers	5	2.2
✓ Other smoking triggers	13	5.8
Advise (app advised the user to quit smoking)	105	46.7
✓ Personalized advice (using user-provided info)	3	1.3
Assess (app assessed the user's readiness to quit)	17	7.6
✓ User could indicate lack of readiness to quit	14	6.2
✓ If so, barriers to quitting were addressed	1	0.4
Assist (app assisted the user with the quit attempt)	215	95.6
Setting a quit date		
✓ Users were asked to pick a quit date	75	33.3
✓ Users received support/feedback on their quit attempt	21	9.3
Support provided		
Reminders about money saved since quitting	82	36.4
Reminders about number of cigarettes not smoked since quitting	73	32.4
Distraction from urges were provided	63	28.0
Reminders about health benefits accrued	38	16.9
Users could interact with other users for mutual support	17	7.6
Referral to quitline or other support group	12	5.3
✓ Recorded personalized message to be played back later	10	4.4
✓ Reminders of their own motivations during difficult times	4	1.8
Information provision		
Informational material was displayed	96	42.7
Links to resources were given	25	11.1
Pharmaceutical products were discussed	41	18.2
Arrange follow-ups (app followed up with the user about the quit attempt)	24	10.7
✓ Checked-in prior to quit attempt	10	4.4
✓ Checked-in after quit attempt	15	6.7
✓ If relapsed, encouraged user to set a new quit day	10	4.4
✓ If relapsed, offered encouragement that quitting takes practice	7	3.1

Table 4. Univariate Association of App Qualities to App Popularity and User-Rated Quality

	Popularity			Perceived quality		
	Number of downloads > 10 000 vs. less			Number of stars (*n* = 173 rated apps only)		
App qualities	*OR*	95% CI	*P*	Est	95% CI	*P*
Basic						
Price (free vs. not)	12.05	2.83% to 51.40%	<.001	−0.17	−0.48% to 0.14%	.27
File size (in MB)	0.98	0.95% to 1.01%	.25	0.00	−0.01% to 0.01%	.75
Free of nuisance factors (vs. not)	2.24	1.14% to 4.41%	.02	−0.12	−0.38% to 0.14%	.37
Included guidance/help section (vs. not)	1.39	0.69% to 2.82%	.36	−0.15	−0.43% to 0.14%	.32
Tailoring in the general approach taken by the app						
Two-way interaction	5.56	2.45% to 12.62%	<.001	0.26	0.00% to 0.53%	.05
Utilization of proactive alerts	3.80	1.54% to 9.38%	.004	0.23	−0.17% to 0.63%	.26
Presence of pre–post quit attempt changes	5.28	2.18% to 12.79%	<.001	0.18	−0.20% to 0.57%	.35
Tailoring in the adherence to the 5As						
Number of As addressed by app (1–5)	1.53	1.10% to 2.14%	.01	0.16	0.03% to 0.30%	.02
Number of As done with any tailoring (1–5)[a]	1.67	1.21% to 2.30%	.002	0.14	0.01% to 0.27%	.03
Number of ways of tailoring 5As content (1–14)[a]	1.35	1.13% to 1.62%	.001	0.08	0.00% to 0.15%	.04

CI = confidence interval; *OR* = odds ratio.

[a]As indicated in Table 3.

and that the level of tailoring done in smoking cessation apps is limited, yet that increased tailoring is preferable to users.

In line with previous research,[11,12] we found that smoking cessation smartphone apps continue to provide predominantly simple tools (eg, calculators, calendars, trackers, distractors) rather than adopting a one-on-one, evolving behavioral counseling style. That is, apps continue to act as tools rather than coaches. Most apps tended to focus on a narrow subset of the 5As, covering, on average, only two of the 5As. Almost every app (96%) addressed "assist," highlighting the role of the app as a narrowly-defined tool rather than a pocket-coach. The other As were addressed by some apps, but noticeably absent were "assess" and "arrange follow-up". At first glance, not assessing readiness to quit is understandable, if the app assumes that a user is ready to quit when he or she is downloading the app. Nevertheless, not specifically addressing readiness to quit represents a missed opportunity to offer congratulations on an important decision, to explore barriers to quitting, or to help move users along towards readiness by, for example, tailoring on the stages of change model.[28] This focus on tool-provision rather than process-oriented counseling may be an unwisely narrow focus, because evidence from other health behavior research suggests that such tool-based apps will result in positive changes only in a very limited subset of patients. For example, a randomized trial examining a calorie-count app showed that app use was only related to weight loss in patients ready to engage in calorie-counting.[29] It is likely that current smoking cessation apps are similarly only helpful to a very limited subset of smokers interested in quitting, namely those who are already highly motivated to quit, and not those who may be more ambivalent.

Arguably one of the greatest strengths of smartphone technology is its ability to be with the smoker 24–7, thereby enabling the app to check in with the user easily and conveniently. While such check-ins might be considered intrusive, our data indicated that utilization of proactive attempts of the apps to reach out to users was actually positively related to app popularity. That finding is encouraging, as it suggests that smoking cessation app users appear to experience behavioral coaching via "push notifications"—messages initiated by the phone's operating system with no action required on the part of the user—as helpful, rather than intrusive. Of course, it is possible that proactive messaging is only perceived as helpful by motivated users, as suggested by a recent randomized trial examining the usefulness of personal health technologies.[30] Yet evidence from mobile smoking cessation trials has also indicated that proactive messaging is related to increased quit success,[1,10,31,32] and is predominantly viewed as helpful and supportive by users.[33,34] These findings are in line with nonmobile intervention work that has shown that proactive smoking cessation counseling is acceptable to smokers,[35] and can help smokers progress from contemplating quitting to taking action,[36] and may enhance quit rates.[37] In that light, the low proportion of apps providing follow-up check-ins (11%) or taking a more proactive interaction style (10%) represents an underutilization of a potentially useful tool.

More generally, the level of tailoring used by the reviewed apps was limited. Very few apps addressed the 5As with any level of tailoring, and even basic levels of tailoring were largely absent. For example, only 33% of apps asked users to set a quit date, and only 9% of the apps provided any support or feedback for a quit attempt. Planning a quit attempt is an active ingredient in achieving success in smoking cessation,[38] including in achieving smoking cessation with the help of an app.[39] Yet currently, most apps remained static throughout the quit attempt. Functionality rarely changed before versus after a quit attempt (11%), users were almost never asked for different information at different times (4%), and information supplied at an earlier time rarely was reflected back by the app to substantiate feedback later (3%). Thus, despite the unique and promising ability of the app to provide just-in-time, tailored feedback, most smoking cessation apps currently do not function in that way.

One could argue that perhaps such a level of tailoring and sophistication might be considered too complex or cumbersome by the user, and may thus be unwanted. Encouragingly, however, it is exactly these types of rarely implemented features that predicted the popularity and user-rated quality of the apps we examined: addressing the quit attempt as a process, as evidenced by addressing more rather than fewer of the 5As, and providing different app functionality before versus after a quit day, were positively associated with both app popularity and user-rated quality. Indeed, doing the 5As, and doing them with tailoring, were the only predictors of an app's user-rated quality. These findings suggest that the consumer market is open to more sophisticated, proactive smartphone apps that coach smokers through a quit attempt.

Limitations

Limitations of this content analysis include its focus on Android apps. Thus, our findings may be specific to Android smoking cessation apps and may not be representative of the whole app market. A previous content analysis, however, has found very little evidence of differences between iPhone and Android smoking cessation apps,[12] suggesting that our findings are likely generalizable. Furthermore, by virtue of being a content analysis, our data were subjectively derived. We sought to minimize subjective biases by the use of independent raters, consensus ratings, and resolution of discrepancies through group discussion. There are also some limitations to using an app's star rating as an indicator of its user-perceived quality. Not all users provide ratings, thereby limiting the generalizability of the star rating, and it is unclear to what degree the star rating on Google Play is safeguarded against attempts to inflate ratings (eg, by single users providing multiple ratings, by apps explicitly soliciting positive feedback while others do not). Nevertheless, while flawed, it is the metric used by consumers to guide their download decision, and thus is a meaningful metric in appraising an app's user-perceived quality. Finally, it should be noted that it is not clear that the delivery of the 5As or the use of tailoring would enhance the effectiveness of smoking cessation apps. While they represent evidence-based best practices in smoking cessation that have shown usefulness in other delivery modes, they may not be applicable to smartphone apps.

Conclusions

Our findings suggest that current, publically available smartphone smoking cessation apps are not particularly "smart": they commonly fall short of providing tailored feedback, and in general act as fairly limited task-specific tools that may be useful to, but do not support users throughout the process of smoking cessation. Juxtaposed with this lack of sophistication of currently available apps is our finding that users appear to value tailoring, as evidenced by the positive association of our tailoring variables with app popularity and user-rated quality. Taken together, our findings suggest that smokers are open to trying "smart" smartphone apps to support smoking cessation.

Supplementary Material

Supplementary Material can be found online at http://www.ntr.oxfordjournals.org

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Declaration of Interests

None declared.

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