Delivering 'Just-In-Time' smoking cessation support via mobile phones: Current knowledge and future directions

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Abstract

Smoking lapses early on during a quit attempt are highly predictive of failing to quit. A large proportion of these lapses are driven by cravings brought about by situational and environmental cues. Use of cognitive-behavioural lapse prevention strategies to combat cue-induced cravings is associated with a reduced risk of lapse, but evidence is lacking in how these strategies can be effectively promoted. Unlike most traditional methods of delivering behavioural support, mobile phones can in principle deliver automated support, including lapse prevention strategy recommendations, Just-In-Time (JIT) for when a smoker is most vulnerable, and prevent early lapse. JIT support can be activated by smokers themselves (*user-triggered*), by pre-specified rules (*server-triggered*) or through sensors that dynamically monitor a smoker's context and trigger support when a high risk environment is sensed (*context-triggered*), also known as a Just-In-Time Adaptive Intervention (JITAI). However, research suggests that *user-triggered* JIT cessation support is seldom used and existing *server-triggered* JIT support is likely to lack sufficient accuracy to effectively target high-risk situations in real time. Evaluations of mobile phone cessation interventions that include *user* and/or *server-triggered* JIT support have yet to adequately assess whether this improves management of high risk situations. While *context-triggered* systems have the greatest potential to deliver JIT support, there are, as yet, no impact evaluations of such systems. Although it may soon be feasible to learn about and monitor a smoker's context unobtrusively using their smartphone without burdensome data entry, there are several potential advantages to involving the smoker in data collection.

Implications

This commentary describes the current knowledge on the potential for mobile phones to deliver automated support to help smokers manage or cope with high risk environments or situations for smoking, known as Just-In-Time (JIT) support. The article categorises JIT support into three main types: *user-triggered*, *server-triggered* and *context-triggered*. For each type of JIT support, a description of the evidence and their potential to effectively target specific high risk environments or situations is described. The concept of unobtrusive sensing without user data entry to inform the delivery of JIT support is finally discussed in relation to potential advantages and disadvantages for behaviour change.

Keywords: mHealth; cue-induced craving; Just-In-Time (JIT) support; Just-In-Time Adaptive Intervention (JITAI); smartphone app; smartphone sensing; SMS text messaging;

Introduction

Different types of smoking cessation support are likely to operate through different mechanistic pathways. Non-pharmacological behavioural cessation interventions potentially have multiple pathways to abstinence. One pathway of particular relevance to mobile phone-based cessation support is via a smoker's actual capability to manage difficult or high risk situations or environments during a quit attempt. Cravings induced by cues from the environment are implicated in almost half of lapses to smoking[1] and contextual factors, such as the presence of other smokers, mood and availability of cigarettes, play a key role in triggering lapse within these environments.[2] Managing cravings, including those induced by environmental cues, is particularly important during the early days of a quit attempt given how strongly early lapse predicts a failure to quit smoking[3, 4] Not smoking in the first week of a quit attempt is associated with more than a five-fold increase in the chance of being abstinent 6 months later.[3] Experimental evidence suggests that this relationship is causal, as manipulating lapse in abstinent smokers independently increases their risk of relapse.[5]

While the most commonly used smoking cessation medications - steady-state medications such as varenicline and the nicotine patch - can help smokers manage background cravings to smoke, they do not appear to be effective at combatting cue-induced cravings.[6] Acutely administered forms of nicotine delivery show evidence of effectiveness to relieve, though not prevent, cue-induced cravings,[6] which may extend to e-cigarettes, though this is untested. The use of cognitive-behavioural strategies, however, is consistently associated with lapse prevention.[6] Implementing a lapse prevention strategy, such as reinforcing one's commitment to quitting, using positive self-talk or avoiding other smokers, can effectively help smokers manage cue-induced cravings,[6-9] particularly when more than one strategy is used in combination.[10] However, smokers are not generally well equipped to be strategic about which lapse prevention strategies they use or when they use them, potentially explaining why the strategies with the strongest evidence base are found to be those least likely to be used.[8]

The capability to manage high risk environments via enactment of lapse prevention strategies is, therefore, likely to be an important pathway to quitting success. However, this is greatly under-researched and it is unclear how such interventions can effectively promote the use of lapse prevention strategies and whether increased strategy use as a result of receiving an intervention translates into abstinence. One significant challenge for traditional intervention approaches to effectively promote lapse prevention strategies has been the mismatch between the relatively static timing of support delivery and the momentary nature of cravings and cues to smoke as the smoker interacts with his or her environment. Such interventions usually rely on smokers to recall appropriate strategies for the situation they are in, often after being informed about them several days or weeks previously, and implement them in-the-moment while experiencing competing demands on their cognitive resources. Such an approach is unlikely to be optimal and, in fact, may do very little to help smokers manage cue-induced cravings. This may be in the process of changing, however, with the portability of mobile phones and people's tendency to have them within reach 90% of their waking lives.[11] Mobile phones, particularly modern smartphones, offer the means for improved synchronisation between the need for support and support delivery. This type of support is commonly known as real-time or Just-In-Time (JIT) support,[12, 13] and mobile phones are currently the optimal communication platform for delivering this.

In this commentary, JIT refers to automated advice or support that a smoker receives close in time to when it is most needed or would be most efficacious. This is typically just before or during when a smoker experiences a craving to smoke or is in an environment that is conducive to them smoking. JIT has been conceptualised as being one aspect of a larger real-time support approach often referred to as Ecological Momentary Intervention (EMI).[14] Mobile phone-based interventions to date have converged on three main methods of triggering JIT support (table 1).

Methods of triggering automated Just-In-Time support and their potential for achieving it

1) *User-triggered:* This is where the smoker decides if and when to request or access JIT support. Common examples include texting a keyword to an SMS text message system for a rapid response advice text e.g. 'HELP' or 'CRAVE',[15-17] calling an Interactive Voice Response (IVR) system ‘helpline’[18] or opening an app to access content.[19]

2) *Server-triggered*: Existing systems that deliver JIT support that is not initiated by the user usually do so according to fixed schedules,[14, 15] random timing,[14] a combination of the two[16-18] or schedules tailored to the individual's self-reported predicted future behaviour or actual past behaviour.[14]

3) *Context-triggered:* A hybrid of approaches 1 and 2 where sensors on or connected to the user’s smartphone are used in real time by the cessation system to interpret the context of an individual's immediate environment and, if deemed to be high risk for smoking, trigger the delivery of support. Despite the anticipation of such support systems for behaviour change,[12, 13] they have been slow to materialise. Currently, there only appears to be one example of such a system; a smoking cessation smartphone app developed at the University of Cambridge, UK, called Q Sense.[20] Q Sense triggers

and tailors the delivery of JIT support using geofencing[21], a location sensing service which is used to determine when smokers enter and dwell within locations where they have smoked previously and are likely to experience cue-induced cravings. Q Sense is trained by the smoker during a short pre-quit date phase. Smokers report their smoking behaviour in real time during this phase, including the key psychological and external environmental antecedents, to enable the system to learn about the environment and geolocation of where they usually smoke.

To date, studies reporting on *user-triggered* JIT support requested via SMS or IVR find these features are used only by a small minority, with very low repeated use patterns that suggest experimentation rather than strategic use.[16-18, 22, 23] Much less has been reported to date on how cessation smartphone apps are used to retrieve in-the-moment support, but a recent study of a cessation app relying on user-initiation to access support content found that the app was opened, on average, only 8.5 times over one month.[19] In their review of 225 Android cessation apps, Hoeppner and colleagues report that 90% of apps rely on users to trigger and access support and do not include any *server-triggered* type alerts.[24] They also found that apps with *server-triggered*/proactive alerts were associated with an almost four-fold increase in the chances of being downloaded.

One clear limitation with most *server-triggered* approaches is the difficulty in accounting for the different routines of smokers and variations in an individual smoker's routine from day to day. Different smokers respond to different environmental cues.[25] Their daily routine and cue exposure may even change after starting a quit attempt and as the attempt progresses over time. Even a smokers' reactivity to environmental cues and intervention content can change over time, as demonstrated by Mason and colleagues.[26] Clearly JIT support triggered by pre-defined rules or schedules will struggle to deliver support at appropriate times. Using an individual's predicted behavioural routine or algorithms based on their recorded behaviour to trigger JIT support could partly help to resolve this limitation. Given that half of lapse episodes occur within 11 minutes of an acute craving,[1, 6] a system using such approaches would need to have very high temporal accuracy to deliver support 'just-in-time'. Realistically, server-triggered JIT support may, therefore, be limited to providing relevant information, advice and encouragement about avoiding smoking that is generally close in time to when it might be useful but not necessarily targeting specific high risk moments.

A system delivering *context-triggered* JIT support using real-time information about the individual's likely exposure to smoking cues or presumed need for support, however, can in principle be robust to between and within-individual differences in routine. Such systems have the potential to intervene immediately before, during or after specific high risk moments. Systems using sensors to adapt and trigger support dynamically are part of a more advanced type of JIT support often referred to as Just-In-Time Adaptive Interventions (JITAI).[27]

How effective is mobile phone-based Just-In-Time support?

Apps appear to be the most common method of accessing cessation support on mobile phones, with more than 200 smoking cessation apps available on the Android Play Store alone[24] and approximately three-quarters of a million monthly downloads for the 98 most popular cessation apps.[28] However, very few have undergone any type of efficacy or effectiveness evaluation to date and mostly they adhere poorly to clinical guidelines.[28] Currently, most evidence for mobile phone cessation interventions comes from evaluations of support systems using telecoms features, primarily SMS text messaging, usually delivering a combination of JIT and more general support. Such interventions are found to increase abstinence by a small but clinically significant amount compared to no intervention,[29] although evidence of a benefit from adding text message support to cessation advice and pharmacotherapy is mixed.[16, 30]

What has yet to be identified, however, is the role JIT support has played in driving the effect of the mobile phone cessation interventions that have been evaluated. In other words, whether any of the effect of these interventions is due to them effectively helping smokers implement lapse prevention strategies to manage high risk situations or environments. Given the low use of *user-triggered* JIT support reported, this approach seems unlikely to have any direct impact, at least among existing interventions. Ideally, the enactment of lapse prevention strategies would be compared in trials between smokers receiving *server-triggered* or *context-triggered* JIT support and those in control or usual care arms. However, the use of lapse prevention strategies is very rarely assessed or reported as part of evaluations. Where this has been done, the evidence to date does not support the efficacy of *server-triggered* JIT support delivered by text message; pregnant smokers receiving a tailored text messaging programme reported using the same number of lapse prevention strategies, including those promoted in the text messages, as those not receiving text message support.[8] Yet, in this trial, there were post-intervention between-group differences in several cognitive determinants found to be predictive of smoking behaviour, namely harm beliefs, self-efficacy and determination to quit. This indicates that the SMS intervention may have had its impact via a different pathway.[17] More data is needed, but these initial findings suggest that delivering JIT support by scheduled SMS may not be an ideal or even effective approach to increase the use of lapse prevention strategies. The same may be true for apps delivering scheduled message alerts given that they are likely to operate in a similar way to SMS text messages. Potentially, the pathway from intervention to abstinence via management of cravings or use of lapse prevention strategies may be, as yet, a grossly under-utilised mechanism in many mobile phone cessation interventions. Improving our understanding of this pathway should inform changes to JIT support within interventions in order to improve their effectiveness.

The road ahead

The ultimate context-aware system is often considered to be one that learns about cue exposure and behaviour unobtrusively without the need for self-reported logging.[31] The act of smoking can already be identified using a wrist-worn accelerometer,[32] and it may soon be possible with off-the-shelf smart watches. Reliably learning about an individual's key psychological and environmental antecedents of smoking without asking them is much trickier however. While there are frameworks for inferring context unobtrusively and developing “anticipatory” mobile interventions,[33] these are largely focused on fairly generic context or activity, such as walking or talking. Emotions can be inferred from sensing data streams, including audio data,[34, 35] but these are limited in terms of emotional range and have battery energy expenditure and potential privacy implications.[36] There is still some way to go, therefore, before your smartphone knows when you are at risk of smoking[12] without you giving it a helping hand along the way.

It is also possible that complete unobtrusive sensing for learning about and identifying cue and behaviour exposure may in fact not be the optimal approach for *context-triggered* JIT support in terms of behaviour change. Excluding the smoker from the process of training a JITAI could omit an active behaviour change technique – self-monitoring.[37, 38] Recording cravings and smoking behaviour could help smokers become more aware and mindful of their craving experience and environmental triggers and it may also increase engagement with the intervention.[39] Recently, a study has shown that high-intensity Ecological Momentary Assessments of cravings to smoke leads to a greater reduction in overall cravings than low-intensity assessments, though with no observed impact on abstinence.[40] Further demonstrations of such reactivity could alleviate a major fear regarding JIT support - that it could inadvertently cue smokers attempting to quit into thinking about smoking and thereby cause cravings.[12, 31] Contrary to this, the evidence so far suggests that making smokers more mindful of their cravings and smoking behaviour could even potentially be protective. Further evaluations, particularly of JITAI, are required to address this question.

It may be optimal, therefore, to include the smoker in the process of training a *context-triggered* JIT intervention or JITAI but in a way that prevents it from becoming burdensome or boring.[41] This could be achieved through a combination of sensor and user input with the opportunity for smokers to self-monitor and review their cravings and smoking behaviour and learn about how this interacts with key context factors. One potential offshoot of such a system is providing nominated supportive others, including smoking cessation counsellors, with information via digital media about the smoker's current experience in attempting to quit. This in turn would provide an opportunity for those supportive others to enhance the tailored support they may provide, including via digital messaging, to augment the impact of the digital intervention.

Summary

Mobile phones promise a potential step-change in the way behavioural cessation support can be delivered through being able to target high risk moments in real time. However, this may only realistically be achieved using context-aware interventions given the idiosyncratic and fast-acting nature of cues that trigger smoking behaviour and the low use of real time support that relies on user activation. While the sophistication of context-aware systems could potentially extend to unobtrusive learning and monitoring of cue exposure and behaviour, this could reduce their impact on behaviour change.

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Competing interests

None declared.

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Table 1 Mobile phone-based methods of triggering automated Just-In-Time smoking cessation support

Approach	**Delivery**	**Potential for tailoring support content**	**Potential for targeting specific situations in real time**	**Examples**
User-triggered	The individual accesses or activates the delivery of support in real time when they deem it is required	Systems can enable individuals to select or request advice and support relevant to their current situation or status. Support can be further tailored to baseline information or information collected during the ongoing support programme	High; though entirely reliant on user activation	• Texting a keyword to an automated SMS text message support system to receive an immediate support text response (e.g. HELP, CRAVE, SLIP, QUIZ) • Calling an automated Interactive Voice Response 'helpline' to receive pre-recorded advice and support • Opening a smartphone app or a website on a mobile browser that provides automated advice and support
Server-triggered	The system or server running the system determines when the delivery of support is required based on pre-determined rules. This includes fixed schedules, schedules pre-determined by the individual or tailored to information provided by the individual either at baseline or during the programme, random timing or a combination of these	Advice and support aimed at helping the individual manage or cope with specific high risk situations can potentially be tailored using baseline information or information collected during the ongoing support programme	Low to moderate; it is challenging to predict an individual's behaviour in real time and requires individual to engage with delivered support	• SMS text messages within a text message support programme or other cessation programme • Interactive Voice Response calls made to the individual • Alerts sent by a smartphone app • Email messages sent to a mobile phone email client • Alerts sent by an automated instant messaging service
Context-triggered	Sensors, either on or connected to an individual's smartphone, determine when the delivery of support is required. Pre-determined rules would usually govern the timing and frequency of support delivery once a high risk context or situation was identified	Advice and support aimed at helping the individual manage or cope with the high risk context or consequence of the context can be tailored to baseline information, information collected during the programme or past/real time sensor data	Moderate to high; requires accurate identification of high risk contexts and the individual to engage with delivered support	• Sensing smartphone app that triggers support in response to the proximity of the individual to a pre-identified high risk location using geofencing (GPS, wifi and cell tower triangulation) • Other context information or situations that could be sensed by a smartphone app include: stress, low mood, presence of other smokers, activity, engagement in habitual behaviours connected to smoking (e.g. after a meal or drinking alcohol)