
Push Away the Smartphone: Investigating Methods to Counter Problematic Smartphone Use

Charlie Pinder

Independent researcher
Birmingham, UK
charlie.pinder@gmail.com

Jose Ignacio Rocca

Universidad ORT Uruguay
Montevideo, Uruguay
jrocca@uni.ort.edu.uy

Benjamin R Cowan

University College Dublin
Belfield, Ireland
benjamin.cowan@ucd.ie

Russell Beale

School of Computer Science
Birmingham, UK
R.Beale@cs.bham.ac.uk

ABSTRACT

There is a growing need to support people to counter problematic smartphone use. We analyse related research in methods to address problematic usage and identify a research gap in off-device retraining. We ran a pilot to address this gap, targeting automatic approach biases for smartphones, delivered on a Tabletop surface. Our quantitative analysis (n=40) shows that self-report and response-time based measures of problematic smartphone usage diverge. We found no evidence that our intervention altered reaction time-based measures. We outline areas of discussion for further research in the field.

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KEYWORDS

Problematic smartphone use; Tabletop;
cognitive bias modification; nonconscious
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technology

INTRODUCTION

This paper discusses the application of nonconscious behaviour change technology [14] to counter problematic smartphone usage in the form of cognitive bias modification (CBM) for approach bias. Approach biases are fast, automatic, nonconscious action urges towards particular cues [10]. CBM for approach biases (CBM-Ap) is any training that targets these approach action predispositions [18]. This paper explores the possibility of retraining smartphone approach bias, i.e. an automatic tendency to reach towards smartphones, using a Tabletop as the intervention technology. The research builds on a requirement for people to not perform anti-smartphone training on their smartphones, and for interventions that do not use limited conscious cognitive resources. Our contribution is a novel experiment applying CBM techniques on a Tabletop, and analysis of related issues of measurement and research in supporting people to address problematic smartphone use.

Table 1: Methods to counter problematic smartphone usage.

	<i>Before</i>	<i>Just-in-time</i>	<i>After</i>
<i>On-device</i>	Restrict access [5, 9]	Real time feedback [2] Timebox current task [5]	Usage information [15, 16]
<i>Off-device</i>	Restrict access [8]	Ambient feedback [1]	Usage information [16]

RELATED WORK

Worldwide smartphone shipments are expected to reach 1.57 billion in 2022 [3]. Meanwhile, research into problematic usage of smartphones shows possible impacts on psychological well-being [17] and sleep disruption [20]. Problematic usage may emerge where smartphone use develops into a habit, because habitual behaviours are automatic and beyond conscious control [12, 14]. Habitual usage can lead to excessive phone checking, which interferes with everyday life when people experience unwanted impulses to check their devices [23]. There is evidence that the mere presence of smartphones can adversely impact cognitive performance [21]. A recent survey (n= 232) found 58% wished to reduce their smartphone usage a little [2], reflected in recent manufacturer releases e.g. Apple’s iOS 12 with tracking and notification restrictions, and Google’s Digital Wellbeing features.

Table 1 summarises existing research into countering problematic smartphone usage across 2 dimensions: *location*, on or off the device; and *timing*, before unwanted usage (e.g. choosing to restrict access), at the time of unwanted usage (e.g. just-in-time warnings), or afterwards (e.g. showing usage data to drive reflection).

On-device studies restricting access to apps to curb problematic use show multiple rule violations [2, 9]. Studies focusing on post-behaviour information e.g. [15, 16] require an additional step for people to process and act on the information for which resources are limited [6]. There is a research gap in using non-smartphone devices in studies. Off-device interventions focus either on directly restricting access to the device [8], or on providing feedback [1, 16], rather than reducing its salience as a behaviour cue.

CBM-Ap approaches seek to train people to reject items that they automatically reach for, but do not want, in favour of wanted items [14]. A review of CBM-Ap research found evidence of effective interventions to reduce approach bias regardless of intervention type (lab vs online) and trial numbers

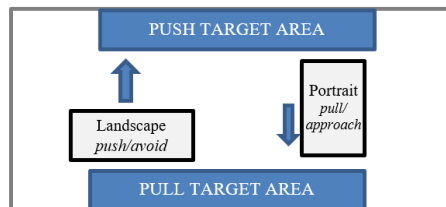


Figure 1: Stylised layout showing approach and avoid areas on Tabletop, measurement trial (push/reject stimuli with landscape frames; pull/accept stimuli with portrait frames)

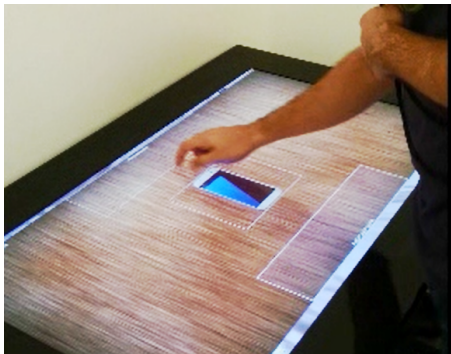


Figure 2: The application in use: a participant pushes away a phone

[4], although few studies reported behavioural outcomes. Despite a few CBM-Ap HCI pilot studies e.g. [13, 19], the technique has not yet been subject to a large-scale long-term trial in HCI.

PILOT

We designed and built a preliminary CBM-Ap intervention on a Tabletop. This device not only allows more expansive accept/reject push/pull gestures than on smartphones, but also the emulation of more realistic situations, and avoids delivering anti-smartphone training on a smartphone itself. Building on evidence that “excessive use of smartphones ... relates to sleep deprivation” [11], our intervention replicated a scenario where people push away smartphones on a bedside table and pull towards them a book. Our hypothesis was that approach biases for smartphone-addicted participants would be reduced by the training intervention. This pilot ran CBM-Ap training trials on a Tabletop, with smartphones as the “avoid” stimuli to be pushed away, and books as the alternative “approach” stimuli to be pulled. It was adapted from Wiers et al.’s alcohol approach-avoidance task (AAT) [22], with evidence the training altered an approach bias to alcohol in heavy drinkers to a small avoid bias.

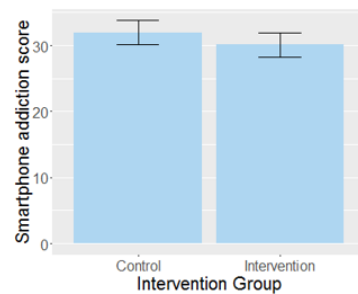
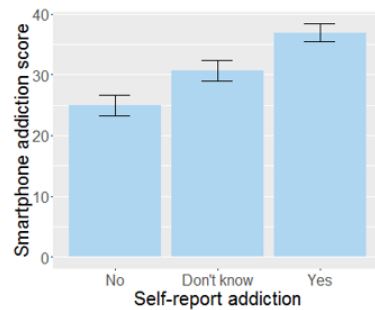
Design. We used a pre-test/post-test control group design. Our independent variables were levels of smartphone addiction; session (pre- vs. post-); and group (control vs. intervention, balanced for smartphone addiction score). Our dependent variable was a measure of smartphone bias, derived from reaction times.

Task. Participants completed a series of trials to accept or reject stimuli. An accept trial meant pulling the stimulus towards them into a target area; a reject trial meant pushing it away into a different target area on the opposite side of the Tabletop, as shown in Figure 1. We logged reaction time data from stimulus appearance in the centre of the table to task completion, i.e. reaching the target area. For measurement trials (all participants), stimuli appeared in landscape or portrait formats and the task was to accept landscape and reject portrait frames as shown in Figure 1. For intervention trials (intervention group participants only), stimuli appeared in square frames, and the task was to accept books and reject smartphone stimuli as shown in Figure 2.

Procedure. 40 participants (age: mean=26.9, SD=4.17; 12 women) were recruited at Birmingham University in the UK. We first measured smartphone addiction using a survey on a laptop, then used a Tabletop accept/reject task to measure and train smartphone approach bias. All participants completed two measurement sessions on the Tabletop (pre and post, each of 40 trials with equal numbers of smartphone and book stimuli). Intervention participants also completed 60 training trials between pre- and post-measurement sessions. Trials were all conducted on a 40 inch Microsoft Pixelsense SUR40 (Microsoft Surface). Stimuli were presented randomly. Participants were encouraged to take a short rest between sessions to alleviate fatigue.

Table 2: Descriptive statistics for smartphone addiction scores (SAS-SV)

	SAS-SV Score	
	Mean	SD
Control	31.95	8.42
Intervention	30.11	7.84

**Figure 3: Mean smartphone addiction scores (SAS-SV) with 1 SE error bars by intervention group****Figure 4: Mean smartphone addiction scores (SAS-SV) with 1 SE error bars by self-categorised addiction**

Measures. Smartphone addiction: we used Kwon et al.'s 10-point shortened Smartphone Addiction Scale (SAS-SV) [7]. Smartphone approach bias: following Wiers et al. [22] this was calculated using the difference in reaction times (RTs) for push (reject) or pull (accept) action for each smartphone stimulus, divided by each user's RT standard deviation.

RESULTS

Smartphone addiction

Participants reported spending an average of 4.93 hours a day on their smartphones (SD=3.97), and checking them on average 54 times a day (SD=45.4). Responses to the question “Do you think you have a maladaptive dependency or addiction over your smartphone usage?” were 17 (42.5%) *Yes*, 16 (40%) *No* and 7 (17.5%) *Don't know*.

Descriptive statistics for the SAS-SV score are shown in Table 2. We found no evidence of a statistically significant difference in smartphone addiction score between intervention and control groups, Welch t-test $t(37.96) = 0.71, p=.48$, as shown in Figure 3. Figure 4 shows that smartphone addiction scores broadly follow self-categorisation of smartphone addiction (No, Don't know, Yes).

Effect of training

From 1,600 pre- and post- measurement smartphone trials with smartphone stimuli, we removed 29 (1.8%) error trials, 12 trials where RT > 5 seconds (0.75%), and 186 trials (11.63%) where RT < 1 second where participants used a “flick” rather than a full-arm gesture. Descriptive statistics for smartphone approach bias score are shown in Table 3 and Figure 5. A positive value indicates an approach bias (pull response is faster); a negative value indicates an avoidance bias (push response is faster).

Table 4 shows the results of a LMER model examining the effect of group (control vs intervention), session (pre vs post), and smartphone addiction (SAS-SV as a continuous covariate) on the smartphone approach bias measure. It included a by-participant random intercept.

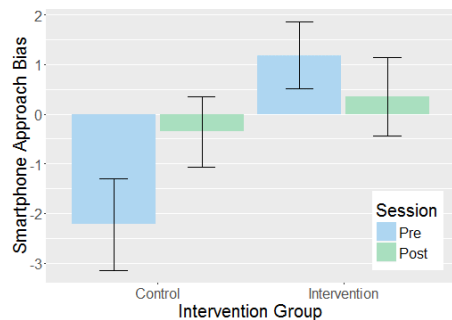
The highest-level statistically significant result was an interaction between intervention group and smartphone addiction score (SAS-SV) ($b=-0.34, SE=0.14, t=-2.52, p=.01$). This indicates that as smartphone addiction score increases, the effect on smartphone approach bias is lower for intervention participants compared to control participants. This effect is shown in Figure 6, which plots fitted model values for smartphone approach bias against smartphone addiction score for our two groups.

DISCUSSION

Overall, our results show no evidence that the intervention was effective in altering approach bias for smartphones. We expected participants reporting higher levels of smartphone addiction to have “trained” themselves in pulling their phones towards them in favour of other objects. Therefore, they

Table 3: Smartphone approach bias score descriptive statistics

Group	PRE		POST	
	Mean	SD	Mean	SD
Control	-2.22	4.24	-0.35	3.24
Intervention	1.19	2.95	0.35	3.45

**Figure 5: Smartphone approach bias score barplot with 1 SE error bars**

would be expected to show positive smartphone approach biases at the outset, which we hypothesised would be moderated by the training in intervention participants. To support the hypothesis, we would have expected a statistically significant three-way interaction between intervention group, session and smartphone addiction, with smartphone addicted users reducing their approach bias between pre and post measures in the intervention but not the control group. We found no evidence of this.

We found a statistically significant interaction between smartphone addiction score and intervention group. The effect of smartphone addiction score on smartphone approach bias differed between our intervention group participants. In particular, a low-addiction score and low-approach bias score was evident in the control group but not the intervention group. The results therefore indicate differing influences of smartphone addiction scores on smartphone approach bias across the control and intervention groups, regardless of the session in which people completed the task.

Limitations. We had a relatively small sample ($n=40$), and our residual measure of random effects was high relative to the effects explained by random variation per user. One source of noise was that the Tabletop was in a social space within the department. We used a smaller number of trials than Wiers et al. [22], because of the risk of user fatigue. Our participants used larger physical gestures, full-arm push and pull, rather than the Wiers et al. joystick.

CONCLUSIONS & FUTURE WORK

Two key research problems remain. We need agreement on a measure of problematic smartphone usage. Our model predictions show inconsistency between self-report (SAS-SV) and reaction-time measures (approach bias): control participants with high SAS-SV scores show an approach bias, but high SAS-SV intervention participants do not. Subjectivity is an issue: usage is *problematic* if perceived as such, but as usage becomes more automatic, it is less accessible to self-report. Secondly, smartphone users re-train themselves to approach their devices through ordinary usage. We encourage further research into and discussion about off-device anti-smartphone training. We intend to repeat our study with more participants, restrictions on the trial gesture to remove the sub-1 second 'flick', and pre- and post- self-report and behavioural measures of smartphone usage.

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Table 4: Smartphone approach bias analysis results

Fixed effects	Estimate	SE	t	p
(Intercept)	-2.44	0.74	-3.28	< .01
Group	3.53	1.08	3.27	< .01
Session	1.98	0.98	2.01	.05
SAS-SV	0.25	0.09	2.73	.01
Group:Session	-2.74	1.43	-1.92	.07
Group:SAS-SV	-0.34	0.14	-2.52	.01
Session:SAS-SV	-0.13	0.12	-1.08	.29
Group:Session: SAS-SV	0.20	0.18	1.12	.27

Random effects	SD
Participant (intercept)	1.20
Residual	3.16

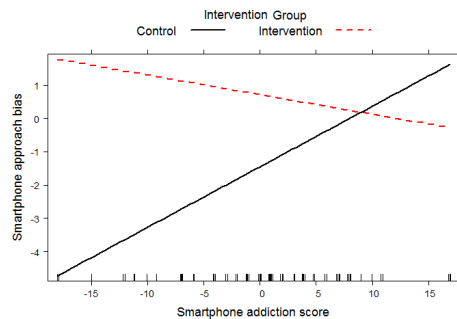


Figure 6: Effect plot for smartphone approach bias and smartphone addiction score across intervention groups. Positive bias scores indicate an approach bias; negative bias scores indicate an avoid bias.

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