Accept the Banana: Exploring Incidental Cognitive Bias Modification Techniques on Smartphones

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ABSTRACT
Cognitive Bias Modification (CBM) techniques show promise in psychology as an attitude, affect and/or behaviour change technique, but have yet to be implemented or evaluated extensively on smartphones. We present an elicitation study on appropriate gestures for accepting and rejecting stimuli on smartphones in line with CBM techniques. We then present a user study on the novel technique of applying CBM in an incidental, unobtrusive way within a smartphone unlock screen. We found evidence that a short course of incidental smartphone CBM alters some measures of food attitudes. Our findings suggest that incidental smartphone CBM techniques have real potential to change behaviour in an unobtrusive way, and we suggest a programme of future research to explore the area further.

Author Keywords
Cognitive bias modification; smartphones; behaviour change technology;

ACM Classification Keywords
H.5.m. Information interfaces and presentation (e.g., HCI): Miscellaneous;

INTRODUCTION
CBM techniques aim to alter the path of existing cognitive processes that are thought to contribute to unwanted emotional reactions and/or behaviour by practicing alternative cognitive paths [12,40].

There is increasing interest in the use of nonconscious behaviour change techniques such as CBM [1,30]. This interest is supported on the theoretical side by Dual Process Theories [9], which suggest that a significant proportion of behavioural decisions emanate from a fast, associative, automatic set of processes that are not accessible to separate conscious processes. This theory contrasts with the rational-action models often cited in Behaviour Change Interventions using Technology (BCITs) e.g. the Theory of Planned Behaviour [3]. Empirical evidence also suggests that rational information-based approaches tend to fail in the long term [13], yet provision of information and other conscious strategies are common BCIT techniques [27,35,38]. Evidence of the abandonment of activity trackers [5,10] supports the DPT prediction of the likely failure of conscious, just-in-time, information based interventions to change habitual behaviour. CBM techniques instead aim to directly alter the automatic processes that drive behaviour.

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RELATED WORK
There are 4 broad categories of CBM:

1. CBM-Attention (CBM-A), which aims to alter an attention bias towards a particular cue and/or away from a particular cue, e.g. [6,17].
2. CBM-Approach (CBM-Ap), which aims to reduce an inherent approach bias away from unwanted cues and/or increase an approach bias towards wanted cues, e.g. [34,39,41].
3. CBM-Interpretation (CBM-I), which aims to reduce negative interpretations of ambiguous information, e.g. [15,24,31,36].
4. CBM-Memory (CBM-M), which seeks to alter the memory of negative information, e.g. [16].

A seminal piece of CBM research is Wiers et al.'s finding that 4x15min sessions of a CBM-Ap training task (push away images of alcoholic drinks, pull towards you images of soft drinks using a joystick) had a small but significant effect on relapse rates in alcoholics when measured after 1 year [39]. A more recent anti-smoking CBM-Ap pilot used a single-session training webpage (push away smoking images, pull towards you neutral images using a mouse). A 4-week post-intervention survey showed a reduction in reported cigarette consumption, dependence and compulsion to smoke compared with a control [41].

Although the research field as a whole is moving towards delivering longer interventions within naturalistic settings [20], few CBM interventions have specifically targeted smartphones or other portable devices. Exceptions include a social anxiety training app using CBM-A [8], which found no significant effects but concluded that smartphones are a viable tool to deliver reaction-time based assessments; and a pilot healthy-eating CBM-Ap tablet game [34], replicating the push/pull paradigm with swipe up/down touchscreen gestures.

There are also several commercial CBM apps claiming to help with social anxiety, problematic eating and smoking [4,22,23], but the evidence for their efficacy is unclear.

We selected the domain of healthy eating because it is a pressing problem: some OECD countries are expected to have 2/3 of their population obese by 2020 [33]. Evidence that CBM can impact this behaviour is provided by Kakoschke et al., who demonstrated that a single-session CBM-A training (employing a modified Dot-Probe Test [21]) can increase both attentional bias for healthy foods and their subsequent consumption [17].

Our approach differs from existing CBM research in the following ways:

- Rather than using the *implicit* reject/accept gestures of the push/pull paradigm [34], we first undertook an elicitation study to explore how users actually attempt to accept/reject items on smartphones.
- We incorporated the CBM training as part of existing smartphone behaviour i.e. as a lock screen app, rather than as a standalone game. This introduces the notion of 'incidental behaviour change': we hijack existing user behaviour, rather than asking them to complete a separate session. We chose unlocking behaviour given evidence that smartphones are unlocked around 57 times per day [14], giving ample opportunity for incidental behaviour change interventions. To our knowledge this is the first intervention to apply CBM techniques in a incidental way on smartphone lock screens.
- We prioritised the showing of the healthy foods over unhealthy foods at a ratio of 9:1 rather than showing equal numbers in order to address the possibility of ironic effects, i.e. that regardless of the action required, showing unhealthy foods might cue users to consume them [2,7]. Our approach is therefore a blend of CBM-A and CBM-Ap since participants are asked to attend more to healthy than unhealthy foods.

Our hypothesis is that CBM to 'accept' healthy food and 'reject' unhealthy food will improve user attitudes towards and ratings of healthy foods and the reverse for unhealthy food. The implicit assumption is that this attitude change will impact on behaviour, but note that we did not test behavioural outcomes at this stage.

STUDY 1: ELICITATION STUDY

Participants and procedure

We recruited 9 students from a UK university (3 females, 6 males). Eight participants were right-handed. All participants had previously used an interactive smartphone.

Participants were given a smartphone running an app that showed eight different screens in succession: either a triangle or a rectangle in one of two colours with the instruction beneath to either "accept" or "reject" the image.

Participants were asked to perform any gesture to reject or accept the shapes. Participants were asked to perform the gesture 3 times before the image changed to the next one to ensure the experimenter coded their gesture correctly.

Results

Table 1 and Table 2 show aggregated results from the Accept and Reject conditions respectively.

Accept gesture	Count	%
Check mark	10	27.8%
Tap inside the shape	7	19.4%
Slide down	6	16.7%
Tap in the word "Accept"	4	11.1%
Double tap inside the shape	2	5.6%
Swipe right	3	8.3%
Slide up	1	2.8%
No gesture	3	8.3%

Table 1 Accept gestures

Reject gesture	Count	%
Cross mark	9	25.00%
Tap in the word "Reject"	3	8.33%
Slide down	5	13.89%
Swipe left	5	13.89%
Swipe right	1	2.78%
Circle and cross	1	2.78%
Tap outside the shape	4	11.11%
Slide up	2	5.56%
Double tap inside the shape	1	2.78%
Double tap outside the shape	1	2.78%
Drawing an arrow	1	2.78%
No gesture	3	8.33%

Table 2 Reject gestures

Discussion

Double tap gestures should be disregarded because this gesture was used to start the experiment and may therefore have had a priming effect. The results show that there is no clear 'natural' accept or reject gesture, but the top gestures in each condition (check mark and cross mark) form a logical pair. Note also that both "slide up" and "slide down" – the most directly mapped gesture from the CBM-Ap push-pull paradigm – appears on both lists, making these gestures unsuitable for accept/reject training. We therefore decided to implement our CBM intervention using a check mark for "accept" and a cross mark for "reject".

It is interesting that there was little consistency in the responses of users: whilst gestures are natural, there is no evidence here for a universally understood positive and negative gesture set.

STUDY II

Method

Participants and design

22 participants (who had not participated in study 1) were recruited from the same UK university (10 females, 12 males; mean age = 29.3 years, *SD* = 9.8 years). All participants with Android mobile phones were invited to take part in the intervention experiment; 12 agreed to do so; other participants acted as the control group (n=10).

Intervention participants (n=12) received an app that on unlock showed an image of either a healthy or unhealthy food as a full-screen overlay. They were instructed to use a check mark to accept healthy foods and a cross mark to reject unhealthy foods. If the correct gesture was performed, the overlay was removed and the participant was shown a brief notification for "accepted" or "rejected". If the participant performed the wrong gesture, the application first asked them to try again, then reminded them of the correct gesture, then removed the overly and showed another reminder of the correct gesture ─see Figure 1 for the "healthy" unlock procedure. The picture shown was randomly selected from a group of 10 healthy food images and 10 unhealthy food images in a ratio of 9:1.

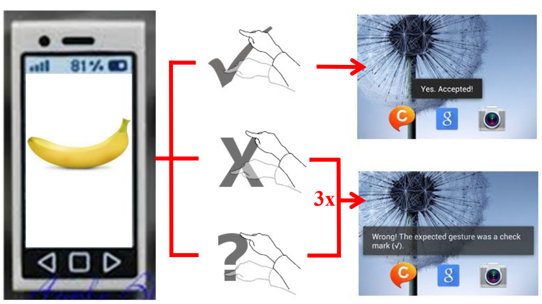

Figure 1 Healthy unlock

Evaluation

Evaluating the impact of BCITs is difficult, particularly in the short term [18]. Measuring the efficacy of behaviour change interventions via self-report measures may not be accurate because of the persistence of the intention-behaviour gap [37]. CBM interventions should measure their impact on the relevant cognitive bias using non-self-report techniques and check for generalisability [20]. Yet the appropriateness of alternative measures of attentional bias, e.g. the emotional Stroop test [29], for studies relating to food consumption is not clear [26]. We therefore selected a pleasantness rating task for the experiment set of healthy (HPR) and unhealthy (UHPR) foods as an implicit measure of attitudes towards them. Alongside this measure, we also implemented two explicit measures of food and food-related attitudes: The Health and Taste Attitude Scale (HTAS) [32], modified to include only the General Health Interest (GHI) on the Health scale, but including all Taste scale components; and a 7-point Likert explicit attitude rating for "healthy food" (HA) and "unhealthy food" (UHA) in general.

Procedure

All participants completed a demographics form and a pre-test questionnaire. Intervention participants were asked to install the app on their phones for 2 weeks or 256 trials (replicated from [17]), whichever happened first. Control participants received no intervention. After 2 weeks, all participants completed a post-test questionnaire identical to the first; in addition, all intervention participants were invited to participate in a semi-structured interview.

The questionnaires comprised:

1. The HTAS as outlined above.
2. An explicit attitude test of both healthy and unhealthy food in general on a 7-point Likert scale rating the following dimensions: important-unimportant, healthy-unhealthy, enjoyable-unenjoyable, harmful-beneficial; satisfying-unsatisfying; pleasurable-unpleasurable.
3. A pleasantness rating on a 7-point Likert scale from "extremely unpleasant" to "extremely pleasant" of the 20 foods pictured in the interventions, 10 healthy and 10 unhealthy.

Results

Quantitative-usage

All participants completed 256 trials. Table 4 shows the percentage of outcomes of all user gestures. The mean error rate (where the participant failed to perform the correct gesture 3 times in a row) was 1.31% (*SD* 1.04). 2 participants (18%) had no trials marked "Incorrect" – i.e. they always performed the correct gesture within 3 tries.

	Correct	Correct 1st try	Correct 2nd try	Correct 3rd try	Incorrect
Mean	98.69	81.50	14.06	3.13	1.31
SD	1.04	5.88	4.28	1.52	1.04
min	96.88	71.88	8.20	1.17	0.00
max	100.00	89.84	21.48	5.47	3.13

Table 4 Percentage of trials with each outcome

Gesture, n^{o}. tries & outcome	Count
Check, 1st try	2116
Check, 2nd try	342
Check, 3rd try	67
Check, Incorrect	25
Cross, 1st try	179
Cross, 2nd try	54
Cross, 3rd try	21
Cross, Incorrect	12

Table 3 Gesture count totals

On average, participants completed 232 healthy food-check trials (SD=*6.27*) and 24 unhealthy food-cross trials (*SD*=6.27). Table 3 shows the totals for each gesture (check, cross) for each possible outcome (correct 1st try, correct 2nd try, correct 3rd try and incorrect). As expected, the results are strongly biased towards healthy food trials.

Quantitative-attitudes

Table 5 shows descriptive statistics for our measures for each intervention group for each session (pre- and post-).

A mixed model 2x2 (intervention x session) analysis of variance on the average HTAS GHI measure found a significant interaction between group and session $F(1,17) = 5.48$, $p = 0.03$. A post-hoc Tukey test showed that there was a significant difference ($p < 0.05$) in the pre- and post- test scores for the intervention group. This confirms our hypothesis that the intervention group's GHI measure would improve post-intervention.

	Intervention				Control			
	Pre		Post		Pre		Post	
	M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
HTAS GHI	4.23	0.76	4.81	0.74	4.53	1.06	4.45	1.07
HTAS taste	3.85	0.47	3.86	0.46	3.83	0.54	3.75	0.64
HFA	6.21	0.45	6.18	0.59	6.12	0.77	5.72	0.59
UHFA	4.99	0.81	4.23	1.20	5.24	1.09	4.23	1.20
HPR	5.73	0.42	5.64	0.85	5.96	0.69	5.64	0.81
UHPR	4.99	0.81	4.23	1.20	5.24	1.09	5.22	0.72

Table 5 Attitude and ratings scores aggregate statistics

Average explicit attitude scores for healthy (HFA) and unhealthy foods (UHFA) were calculated for each participant (reverse-scoring the harmful/beneficial component) and mixed model 2x2 (intervention vs session) analyses of variance were calculated for each score. No significant differences were found for this score for the interaction between intervention and session.

Quantitative-ratings

Average pleasantness ratings for healthy foods (HPR) and unhealthy foods (UHPR) were calculated for each participant, and mixed model 2x2 (intervention x session) analyses of variance were calculated for each score. No significant differences were found for this score the interaction between intervention and session, contrary to our expectation that repeatedly viewing the healthy food items would have an effect on HPR both from the CBM intervention and the mere exposure effect.

Qualitative-Interviews

6 of the 12 intervention participants completed a post-intervention interview via email. Interestingly, 5 of the 6 respondents felt that the app supported them to make conscious healthy food choices. Requests for feature improvements included personalisation of the healthy/unhealthy food (3 participants), with one participant struggling to recognise an avocado. One participant reported frustration with gesture recognition, particularly when they were in a hurry.

DISCUSSION

Our hypotheses were that the intervention group's HTAS scores and healthy food ratings would increase following intervention relative to the control group. The results show that this only held for HTAS GHI scores. No other evidence for changes was found, despite the large number of healthy 'accept' trials completed as shown in Table 3, which we expected to at least have some impact on positive ratings via the mere exposure effect [42]. Nevertheless, the HTAS GHI score questions are somewhat unrelated to the specifics of the experiment (i.e. do not ask about particular healthy/unhealthy foods), indicating that the intervention may have generalised effects.

FUTURE RESEARCH

Repeating the experiment with a larger group and a longer period of intervention is an important next step. A longer intervention period would also support the automaticity of response to a healthy or unhealthy cue as distinct from the participants' perception of a conscious choice: automaticity in behaviour may take 66 days to plateau [19].

Evaluation measures

Future experiments should measure efficacy directly via a behavioural measure (i.e. food consumption) because of the difficulties of ascertaining an uncontroversial implicit measure of food attitude [26], the intention-behaviour gap [37], and the habitual nature of food consumption. We accept that this is difficult to capture in an in-the-wild experiment without self-report, which may be subject to bias [11].

Personalisation

Future experiments should require users to provide their own food images. A stronger effect may thus be obtained because healthy and unhealthy targets will reflect each user's preferences, also addressing the avocado recognition problem. Further, using photos of foods in naturalistic contexts may also result in a stronger effect since the context may also form part of the food-cuing process [28].

Increasing interaction

CBM techniques could be further embedded into existing interaction gestures, e.g. integrating an unwanted cue into the swipe gestures inherent in an image gallery interaction. The *physical* push/pull effort involved in the CBM-Ap paradigm as implemented by Wiers at al. [39] is important: future work should explore the use of motion gestures (e.g. [25]) to accept/reject wanted/unwanted stimuli on smartphones.

In summary, we have demonstrated the feasibility and potential impact of an incidental CBM intervention on smartphones to promote healthy eating that integrates unobtrusively into users' lives. We feel the area of research has strong potential to impact on user behaviour and serves as an important contribution to the field of nonconscious behaviour change techniques.

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