TARGETING THE AUTOMATIC: NONCONSCIOUS BEHAVIOUR CHANGE USING TECHNOLOGY

by

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“If it weren't for the people, the god-damn people … always getting tangled up in the machinery. If it weren't for them, the world would be an engineer's paradise.”

Kurt Vonnegut, Player Piano

“No alarms and no surprises, please”

Radiohead, No Surprises

ABSTRACT

Digital interventions have great potential to support people to change their behaviour. However, most interventions focus on strategies that target limited conscious resources, reducing their potential impact. We outline how these may fail in the longer-term due to issues with theory, users and technology. We propose an alternative: the direct targeting of nonconscious processes to achieve behaviour change.

We synthesise Dual Process Theory, modern habit theory and Goal Setting Theory, which together model how users form and break nonconscious behaviours, into an explanatory framework to explore nonconscious behaviour change interventions. We explore the theoretical and practical implications of this approach, and apply it to a series of empirical studies.

The studies explore nonconscious-targeting interventions across a continuum of conscious attention required at the point of behavioural action, from high (just-in-time reminders within Implementation Intentions) to medium (training paradigms within cognitive bias modification) to low (subliminal priming). The findings show that these single-nonconscious-target interventions have mixed results in in-the-wild and semi-controlled conditions.

We conclude by outlining how interventions might strategically deploy multiple interventions that target the nonconscious at differing levels of conscious attention, and by identifying promising avenues of future research.

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CONTRIBUTING PUBLICATIONS

This thesis is based partly on the published works outlined below.

Journal papers

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Conference Papers – Alt.chi

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Awarded a Best of Alt CHI "Best Provocation Award".

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Charlie Pinder. 2013. Breaking and forming habits using technology: theoretical pointers from psychology. In 1st Habits in Human Computer Interaction Workshop, BCS HCI '13.

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LIST OF ABBREVIATIONS

AAT alcohol approach-avoidance task

BAF Behaviour Alteration Framework

CBM Cognitive Bias Modification

CBM-Ap Cognitive Bias Modification for approach bias

CBM-A Cognitive Bias Modification for attention bias

DBCI Digital Behaviour Change Interventions

CI Confidence Interval

DPT Dual Process Theory

EMM Estimated Marginal Mean

GFF Goal Failure Framework

GHI General Health Index (subscale of HTAS)

GLMER Generalised Linear Mixed-Effects Regression

HFA Healthy Food Attitude

HTAS Health and Taste Attitude Scale

HFIR Healthy Food Image Rating

HWK Hollenbeck, Williams and Klein measure of goal commitment

II Implementation Intention

LMER Linear Mixed-Effects Regression

NDBCIs Nonconscious Digital Behaviour Change Interventions

Mixed-ANOVA mixed (i.e. including fixed and random terms) ANalysis Of VAriance

RT Reaction Time

SD Standard Deviation

SE Standard Error

SNS Social Networking Site

UHFA Unhealthy Food Attitude

UHFIR Unhealthy Food Image Rating

1. INTRODUCTION

OVERVIEW

This thesis explores the use of technology to target nonconscious processes that affect behaviour. Changing human behaviour is a highly complex problem, and many interventions fail in the long term. Growth in personal technology has piqued interest in using technology in Digital Behaviour Change Interventions (DBCIs). However, DBCIs have not been a panacea. We outline how behaviour change failures can be understood because of issues with theory, users and technology.

We argue that user issues in DBCIs stem broadly from an overreliance on conscious rather than nonconscious influences on behaviour. We outline Nonconscious Digital Behaviour Change Interventions (NDBCIs) as an alternative: technology-based interventions that target nonconscious, automatic cognitive processes, with the goal of behaviour change. We present the Behaviour Alteration Framework to illustrate how Dual Process Theory, modern habit theory and Goal Setting Theory indicate how nonconscious processes can impact on behaviour, and strategies to target them. We explore technology-based implementations of three promising strategies: Implementation Intentions, cognitive bias modification and subliminal priming.

Our two key research questions are: what are the nonconscious influences on behaviour, and what are the opportunities to intervene with these influences to change behaviour; and how can technology best exploit these opportunities to intervene in a user-friendly way?

BACKGROUND AND MOTIVATION

Humans persist in behaving in ways they know are harmful [Keeney 2008]. The World Health Organisation identified several persistent lifestyle behaviours which impact severely on health, accounting for 61% of worldwide cardiovascular deaths, including “alcohol use, tobacco use, high blood pressure, high body mass index, high cholesterol, high blood glucose, low fruit and vegetable intake, and physical inactivity” [WHO 2009]. Meanwhile, pervasive computing technology offering multiple detection methods and intervention points becomes cheaper and more widely owned, providing great potential for DBCIs to change behaviour. Smartphone ownership reached 69% in the UK in 2015 [Ipsos 2015], worldwide mobile phone shipments reached 1.86 billion in 2017, and are predicted to rise into 2018-9 [Gartner 2018], and strong growth is predicted in the wearables market [Lee et al. 2015; Wei 2014]. Smartphone DBCIs are prevalent [Fiordelli et al. 2013; Klasnja and Pratt

2012; Lathia et al. 2013], and more UbiComp DBCIs are emerging e.g. [Adams et al. 2015; Khot et al. 2015; Kim et al. 2016].

Developing effective DBCIs is constrained by issues with theory, users and technology. DBCIs do not always apply theory-driven solutions, partly because of a great number of different theories, frameworks, models and techniques. DBCIs also fail because of a mismatch between users and the intervention. Most DBCIs focus on behaviour-change strategies that target conscious processes: tracking, goal setting, reminders and providing information are frequently-used techniques [Cowan et al. 2013; Stawarz et al. 2015]. However, users have limited conscious cognitive resources in both conscious attention [Norman and Shallice 1986] and in short-term working memory [Cowan 2010; Cowan 1988]. Further, users may not respond immediately to 'just-in-time' interventions [Pejovic and Musolesi 2014]. They may experience reactance, where users reject interventions to preserve behavioural autonomy [Brehm 2009]. Users tend to abandon pervasive trackers in the long term, partly because of gaps between user expectations and the technology [Goodyear et al. 2017; Yang et al. 2015]. Technological issues persist: accurate detection of contextual triggers and behaviour are difficult problems that UbiComp has yet to solve [Rogers 2006]. This thesis addresses the theory issue by providing an illustrative framework for interventions; and addresses the user and technology issues by exploring alternatives to conscious-process targeting.

THE APPROACH

We argue that understanding nonconscious processes is central to explaining why behaviour change is difficult and why conscious behaviour change interventions tend to fail. We explore multiple NDBCIs as an alternative approach. Similar arguments focusing on nonconscious processes are starting to emerge in the domain of health policy [Kelly and Barker 2016] and the health behaviour domain more broadly [Marteau et al. 2012; Hollands et al. 2016], but the approach has yet to be applied rigorously to DBCIs. The nonconscious research that is starting to emerge in HCI tends to focus on custom-built UbiComp solutions, e.g. Adams et al.'s study to change "mindless" eating behaviour [2015], and Amores & Maes' essence prototype necklace that uses smell as a nonconscious prime [2017] . Our research, by contrast, focuses on using *existing* technology, including smartphones and Tabletops, to deliver NDBCIs.

We address the three issues identified above: theory, users and technology. To answer the first research question, what are the nonconscious influences on people's behaviour, we first focus on theory. In Chapters 2 and 3 we construct a theory-driven illustrative framework, the Behaviour

Alteration Framework, BAF, from a review of the ability of common behaviour change theories to deal with nonconscious behaviour. The BAF synthesises Dual Process Theory, modern Habit Theory and Goal Setting Theory to explore how nonconscious and conscious processes together drive behavioural decisions.

To answer the second research question, how can technology alter nonconscious processes, we then focus on technology and users. We use the BAF to map current DBCI research onto intervention points to identify technology-based research opportunities, and highlight the state of the art (Chapter 3). We then explore a subset of the technology-based intervention opportunities in a series of NDBCI studies (Chapters 4-6). We carry out a series of experiments and qualitative analyses to better understand how to deal with issues of limited conscious capacity, reactance and user-technology mismatches. Our NDBCI studies span a continuum of cognitive load at the point of behavioural action, in line with Dix et al.'s intentional interaction spectrum [2010:651]. We have defined NDBCIs as any intervention *targeting* nonconscious processes. The intervention itself may be not obvious to the user and place little cognitive load on their resources, e.g. the use of subliminal priming (Chapter 6), or it may impose a high cognitive load by requiring conscious attention at the point of action (e.g. just-in-time behavioural reminders trying to support users to form new habits, Chapter 4), or lie in between the two (e.g. opportunistic incidental interactions, where user actions performed for some other purpose are co-opted for use [Dix 2002; Dix et al. 2010:653; Ding et al. 2016]).

Table 1:1 shows the experiments ranging across cognitive load from high (interruption systems), to medium (pre-behaviour training), to low (subliminal priming). Table 1:2 gives an expanded overview of the individual experiments including their domain, platform and intervention delivery types.

	Cognitive load		
	High	*Medium*	*Low*
Characteristics	Just in time alerts. Direct attention and action requests from system	Intervention co-opting other activity; some conscious attention requested. Training without direct behavioural prompts.	No conscious attention or direct behaviour requested;
Example	Context-aware behaviour reminders (Chapter 4)	Cognitive Bias Modification training (Chapter 5)	Subliminal priming (Chapter 6)

Table 1:1 DBCIs mapped across continuum of cognitive load of intervention

Approach	*Research Question*	*Domain*	*Platform*	*Intervention delivery*	*Cognitive load*	*Experimental context*	*Research techniques*	*Chapter*
Implementation intentions	How can context-aware technology support Implementation Intentions?	General health	Smartphones	Just-in-time	High	In-the-wild	Longitudinal experiment; survey	4
Cognitive Bias Modification	Can incidental cognitive bias modification alter implicit attitudes to food?	Healthy eating	Smartphones	Opportunistic incidental interaction	Medium	In-the-wild	Elicitation study; longitudinal experiment; semi-structured interviews; survey	5
Cognitive Bias Modification	Can cognitive bias modification alter approach biases to smartphones?	Smartphone addiction	Tabletop	Training	Medium	Semi-controlled	Survey; single session experiment	5
Subliminal Priming	Can incidental subliminal priming on smartphones cause nonconscious goal activation?	Physical activity	Smartphones	Opportunistic incidental interaction	Low	In-the-wild	Longitudinal experiment	6
Subliminal Priming	Can subliminal priming increase stimulus preference or selection?	General	Smartphones	Task	Low	Semi-controlled	Technical feasibility study; single session experiments	6
Goal setting	How can technology support users to create automatable goals?	Physical activity	Smartphones	Task	Low	In-the-wild	Survey	7

Table 1:2 Experimental approaches overview

This thesis starts at the high cognitive load end of the continuum with an exploration of the application of context-aware technology to Implementation Intentions. After finding evidence of user intelligibility issues, frustration with disruptive approaches and low interest in context-aware reminders, we moved to the right to explore medium-load DBCIs with lightweight training tasks attached to unlock behaviour. We uncovered further user issues with an opportunistic system that potentially interrupted other activities, so we then explored time-shifting the cognitive load to a training task intended to alter future problematic behaviour without further reminders or intervention.

Finding mixed results for this intervention, and being unable to disambiguate whether the issues were rooted in conscious or nonconscious processes, we then moved to the far right of the continuum to explore in depth the possibilities afforded by low-cognitive-load interventions that explicitly target nonconscious processes in the form of subliminal priming. We found little evidence of stable effects for this approach.

Finally, drawing on our results, in Chapter 7 we outline how technology can strategically combine high- and medium-cognitive load approaches to achieve low-cognitive load goal automation.

Research questions

This thesis addresses the following broad research questions:

1. What are the nonconscious influences on behaviour, and what are the opportunities to intervene with these influences to change behaviour?
2. How can technology best exploit these opportunities to intervene in a user-friendly way?

The first research question is addressed from a theoretical level, synthesising existing theory and research to map out potential approaches. We then address the second question by running multiple experiments in the NDBCI research space.

Research methodology

This thesis uses a mixed-methods approach [van Turnhout et al. 2014], combining both quantitative and qualitative research methods to explore the problem space of NDBCIs. The different techniques are shown in Table 1:2.

Most of our quantitative studies use a pre-post-control design to avoid interference between conditions, and for most of our subliminal experiments to avoid participants becoming aware of the

purpose of the intervention by detecting differences in the conditions [Hornbæk 2011]. Exceptions were pilot 4.1 which had no control, and experiment 6.4, which used a within-subjects design. We based the latter on an existing psychology experiment and so used the same design to ease comparison with the original.

Statistical approach

Pre-post-control design introduces temporal pseudoreplication [Crawley 2005], since we gather repeated pre- and post- measures from the same individuals within each intervention group. To deal with this, in line with Larson-Hall [2016], we use mixed ANOVAs on mean data (e.g. for Likert scale means), with intervention group as a between-subjects factor, and time of measure as a within-subjects factor, and (generalised) linear mixed-effects regression ((G)LMER) models for reaction time and binary data. (G)LMER are used because they allow us to model random effects, for example random variations within individual participants. Judd et al. argue that including random variations is particularly important to deal with stimulus sampling issues within experiments on implicit reactions [2012]. (G)LMER models also make more realistic assumptions than ANOVA (e.g. they do not assume sphericity), provide higher power and broader validity [Larson-Hall 2016], and can analyse individual rather than mean responses [Lo and Andrews 2015]. Bolker et al. argue that (G)LMER are the most appropriate method to analyse non-normal data that involves random effects [2009]. For binary outcomes, GLMERs help to avoid spurious results generated by using ANOVA to analyse proportions or percentages, and improve statistical power compared to ANOVA [Jaeger 2008]. The exception to (G)LMER-for-reaction-time-data rule is in Experiment 5.3, where in line with existing approaches, we calculated an approach-bias score based on median RT values.

All statistical analysis was run on R, version 3.1.1 [Pinheiro et al. 2014]. Mixed ANOVAs were run using afex [Singmann 2017]. (G)LMER models were constructed using lme4 [Bates et al. 2015], with *p* values generated by the lmerTest package [Kuznetsova et al.], which use Satterthwaite approximations for degrees of freedom. There is some debate over the appropriate measurement of how well a (G)LMER model fits the data, i.e. how much variance in the data is explained by the model [Nakagawa and Schielzeth 2013; Colin Cameron and Windmeijer 1997]. In line with Baayen & Milin [2015], for non-binomial models we provide a simple pseudo-R-squared measure (R^2_{PS}) which estimates the correlation between fitted and observed values. For binomial models we provide marginal R squared (R^2_M) which estimates how much the model's fixed effects explain data variance, and conditional R squared (R^2_C) which estimate how much the model explains variance as a whole,

from the MumIn package [Barton 2017]. However, we also note that providing R^2 measures is controversial [Bates 2006]. We provide *p* values because it is convention within HCI, and R^2 values to give some simple indication of model fit. However, we note that the provision of *p* values for (G)LMER is also controversial and no Bonferroni corrections [Wolfram] were made, increasing the chance of a Type 1 error. We therefore also give estimated marginal values for the fixed parts of our models using the lsmeans R library [Lenth 2016], although note that estimated marginal mean CIs can be misleading because they do not include random effects.

We followed Baayen & Milin to use a combination of model comparisons and outlier removal to refine our models [2015]. They advocate minimal data trimming at the outset, combined with model criticism where model residuals were visually inspected and trimming applied if problems are identified. We started with an LMER model on data with impossible values removed; if model residuals violate normality (determined via a Shapiro-Wilk test and/or visual inspection), we investigated alternative GLMERs to fit the data in line with Lo and Andrews [2015]. We trimmed GLMER model residuals to within 2.5 standard deviations of the mean where visual inspection of GLMER residuals indicated violations of homogeneity of variance in line with Baayen & Milin [2015]. Where multiple GLMERs converged, we used model comparison on their Bayesian Information Criterion (BIC) values, an indicator of model fit [Bates et al. 2010:4], to select the model of best fit. Most (G)LMERs use dummy coding for factor contrasts where a baseline (e.g. a control group) is available. Exceptions to this are noted in the text.

Definitions

We use the term “nonconscious” in preference to “unconscious” because of the latter’s association with Freudian psychology. We define nonconscious behaviour as behaviour arising from cognitive processes that run regardless of conscious intention, outside mental awareness. The focus of this thesis is on nonconscious goal pursuit and habits as key automatic drivers of behaviour. We define habit as a learned, automatic impulse to behave in a certain way, in response to stable contextual cues, and automatic goal pursuit as the activation and enactment of goal-related behaviour without conscious intent. This is explored in more detail in Chapters 2, 3, 6 and 7.

Collaborations

To avoid switching between "I" and "we", I have used the term "we" throughout. Parts of chapters 4 and 5 report student projects, where the original ideas were mine, and I supervised the projects, but the students carried out the development and data-gathering themselves. Specifically, Study 4.1 Implementation Intention Pilot, Experiment 5.1: "Accept the banana" and Experiment 5.3: "Push away the smartphone" were student projects (with MSc students Adhi Wicaksono (4.1), Rosa Lilia Segundo Diaz (5.1) and Jose Ignacio Rocca (5.3)), while the related work and discussion sections, data analysis and additional qualitative surveys 4.2 and 5.2 were my own work. An MSc student, Po-Wei Chen, carried out data-gathering only for experiments 6.3.B and 6.4. I analysed all the data in this thesis, and I am first author on all publications arising from it.

Contributions

The primary contribution of this thesis is to integrate knowledge from multiple fields to establish a framework for DBCIs to include nonconscious processes in their interventions and to explore these in multiple in-the-wild and semi-controlled studies. Specific contributions are:

- A Behaviour Alteration Framework that assimilates a set of theories to illustrate intervention strategies for DBCIs that can incorporate nonconscious processes (Chapter 3)
- The practical application of the framework in a series of NDBCI studies (Chapters 4-7).
- An in-depth study of the feasibility of subliminal priming on smartphones (Chapter 6.
- An exploration of the sources of goal setting failures with technology (Chapter 7).
- A synthesis of the results and a research agenda for future DBCIs that can incorporate nonconscious processes (Chapter 8).

The findings have implications for researchers in behaviour change fields, including HCI, who wish to look beyond conscious intentions to altering nonconscious processes. The framework and principles distil much related literature and practice to aid the practical application of techniques from psychology labs to both in-the-wild and semi-controlled interventions. Overall, we found mixed evidence for the efficacy of subliminal priming, the lowest-cognitive load intervention, and evidence that single-target higher-cognitive-load interventions still face user and technical restrictions. We therefore argue in Chapter 7 that a good future strategy is to strategically deploy multiple

interventions that require different levels of cognitive attention. We suggest shifting away from just-in-time or opportunistic training to focus instead on high- and medium- load creation and rehearsal processes to automate goals, such that they will be activated by the user's context in a low-cognitive load fashion.

THESIS STRUCTURE

Chapter 2 sets out the theoretical underpinnings of the nonconscious approach. It explores how the study of nonconscious processes such as habits can help to understand behaviour change failures in the longer term, and outlines relevant domains for intervention. We present an overview of the main theoretical approaches in DBCI research to determine their suitability to target behaviour via nonconscious processes. We highlight three theories that together explain both conscious and nonconscious intervention points for sustainable behaviour change: Dual Process Theory, modern Habit Theory and Goal Setting Theory.

Chapter 3 synthesises these theories into a framework (the Behaviour Alteration Framework, BAF) to illustrate the potential intervention points for technology and outline the state of the art for each strategy. We outline three promising strategies of research: specialised action plans called Implementation Intentions; Cognitive Bias Modification; and subliminal priming.

The next 3 chapters outline a series of NDBCIs based on these strategies. Chapter 4 describes a pilot on smartphones and a qualitative survey that together explore how context-aware technology can support Implementation Intentions. Chapter 5 describes two studies and other exploratory work in retraining the nonconscious via Cognitive Bias Modification, one experiment on smartphones, and the other on a Tabletop surface. Chapters 4 & 5 present exploratory work into NDBCI strategies of Implementation Intentions and Cognitive Bias Modification respectively. Together with the qualitative research in both chapters, they provide interested researchers with a starting point for future research, from domains of interest to multiple potential applied methods of intervention.

Chapter 6 presents a deeper investigation into the feasibility of subliminal priming techniques on smartphones, with multiple experiments from pilots in-the-wild to larger-scale experiments in semi-controlled conditions. The final experimental chapter, Chapter 7, uses a qualitative analysis of physical activity goals users form on smartphones together with the lessons learned from previous chapters, to outline how multiple NDBCI strategies can work together to achieve goal automation as a promising future strategy. The thesis concludes in Chapter 8 with an overall discussion and a future research agenda.

2. BACKGROUND AND RELATED WORK

OVERVIEW

This chapter analyses why nonconscious behaviours such as habits are important to behaviour change interventions. It:

- defines nonconscious behaviours including habits and nonconscious goal pursuit, outlines evidence for their prevalence, identifies relevant domains, and summarises the mechanisms by which these behaviours can become persistent; and
- assesses key behaviour change theories for their ability to support interventions to alter nonconscious behaviours.

THE IMPORTANCE OF NONCONSCIOUS BEHAVIOURS

Conscious control of behaviour runs along a continuum, from cognitively-intensive tasks that require high levels of concentration to behaviours that people can perform without thinking. For example, consider learning to ride a bicycle. At the outset, performing the behaviour involves slow, effortful concentration, checking and multiple errors. Over time, with sufficient repetition, the same behaviour can be done effortlessly alongside other cognitively demanding tasks such as composing a text[1].

DEFINITION

Bargh & Chartrand defined four properties of automatic behaviour: it is unintentional; uncontrollable; performed without awareness; and efficient [1999]. Automatic behaviour comprises a broad spectrum of behaviour, from reflexes and compulsive behaviours to habits and goal-related automatic behaviours [Verplanken and Aarts 1999]. This thesis focuses on the last two.

Habitual behaviour is learned behaviour that is “frequently repeated, has acquired a high degree of automaticity, and is cued in stable contexts” [Orbell and Verplanken 2010]. Nonconscious goal pursuit is the automatic activation and enactment of goal-directed behaviour [Hassin et al. 2009]. Automaticity means such behaviours can be performed nonconsciously, i.e. “enacted with little conscious awareness” [Orbell and Verplanken 2010].

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[1] We would not recommend texting and cycling.

In contrast to common usage of the word habit, we define it as a context-response link driving the behaviour, rather than behaviour itself. The occurrence of the context triggers a response impulse. A habit is therefore a disposition to perform a given behaviour [Gardner 2015; Neal et al. 2006]. Habitual behaviour is the behaviour that results from this impulse.

Although automatic behaviours are triggered nonconsciously, people are not necessarily unaware of their actual behaviour. Instead, they tend to be unaware of the internal nonconscious processes driving their behaviour [Stanovich 2005], such as the context-response associations [Wood and Rünger 2016]. This inability to introspect underlying processes makes such behaviours difficult to change: if the cause of an unwanted behaviour is not clear, then neither is the solution.

Nonconscious behaviour prevalence and domains

Nonconscious behaviours such as habits are highly prevalent and structure much of everyday life [Wood et al. 2014]. People report 43% of their behaviours as being performed without conscious thought [Wood et al. 2002], study 2.). Habitual behaviours span multiple domains: health [Gardner 2015], including eating [Robinson et al. 2013; Rothman et al. 2009; Wansink 2010], exercise behaviour [Conroy et al. 2013; Aarts et al. 1997] and physical activity [Rebar et al. 2016], behaviour of healthcare workers [Nilsen et al. 2012]; environmental behaviour [Klöckner 2013]. Habits have even been shown to be important in our use of technology [Limayem et al. 2007; Bayer and Campbell 2012; Oulasvirta et al. 2012], including our participation in online communities [Wohn et al. 2012] and use of smartphones [van Deursen et al. 2015].

Despite increasing interest in nonconscious behaviours in health psychology [Gardner 2015], few general behaviour change interventions currently use habit formation theory [Lally et al. 2008]. Likewise, few DBCI apps target habit constructs [Stawarz et al. 2015] or general nonconscious behaviours [Adams et al. 2015]. Adams et al found of 176 DBCI papers, only 11 targeted nonconscious behaviour, and only 2 mentioned related theory [2015]. Orji and Moffatt found of 85 health domain DBCIs, only 3 targeted habits [2016].

A challenge and an opportunity

Changing behaviour via nonconscious behaviours is both a challenge and an opportunity. The challenge is to break persistent unwanted nonconscious associations between contexts and behaviours. The opportunity is to use the same association mechanism to establish wanted nonconscious behaviours that are similarly resistant to change.

Habit formation can enable the maintenance of wanted behaviours [Sheeran et al. 2017], since habitual behaviours are the default behaviour when people are unable or unwilling to make effortful decisions about how to behave [Neal et al. 2013]. They are performed automatically with little cognitive effort. These properties mean that DBCIs that can successfully form 'good' habits and break 'bad' habits are likely to have long-lasting behavioural effects [Verplanken and Wood 2006; Rothman et al. 2009; Lally et al. 2011; Sheeran et al. 2017]. However, people often return to their unwanted behaviours over time [Bouton 2014]. This failure to sustain behaviour change is likely because of a lack of focus on automatic processes [Marteau et al. 2012] including habits. Behaviour change research tends to use deliberative interventions that rely on limited conscious resources: the provision of information is the most common DBCI technique [Webb et al. 2010b]. Such interventions are often unsuccessful in the long term [Hillsdon et al. 2002; Verplanken and Wood 2006; Davis et al. 2015b]. Reflecting this, habits are one of the key challenges for behavioural change policy [Jackson 2005].

Theories of behaviour change

A critical component of addressing this gap is by understanding the key behavioural theories that contribute to our understanding of behaviour change at present and how they apply to nonconscious behaviours. This section reviews the use of theory in behaviour change in general and in DBCIs.

Theory use in behaviour change research

The behaviour change research landscape is cluttered with multiple theories, frameworks, models, techniques, strategies and patterns. Table 2:1 demonstrates the issue: just a few behaviour change researchers have identified tens of different behaviour change techniques, multiple ways behaviour might change, and numerous related theories and models.

Theory enables researchers to be more explicit about their assumptions, strategies and intervention targets [Rimer and Glanz 2005]. Despite—or perhaps because of—the number of competing models, there is a persistent lack of reference to theory in behaviour change research. The problem extends to DBCI research. Multiple reviews of DBCI research have found less than 50% specified a theoretical basis [Wiafe and Nakata 2012; Orji and Moffatt 2016], while Stawarz et al.'s review of habit formation apps found few that used features from habit theory [2015]. Many interventions that claim to be based on theory fail to make explicit how the theory relates to the intervention or use theoretically predicted measures as evaluating criteria [Michie and Prestwich 2010; Harris et al.

2011]. Likewise, few studies provide an in-depth understanding of the underlying mechanisms of behaviour and attitude change [Segerståhl et al. 2010; Riley et al. 2011], and few persuasive systems justify in detail their choice of behaviour change strategy, or the impact they are expected to have on their users [Foster et al. 2011].

Number of ways behaviour might change	35 [Fogg 2009a] 26 [Abraham and Michie 2008]
Number of behaviour change techniques, strategies or patterns	101 [Lockton et al. 2010] 93 [Michie et al. 2013a] 56 [Wiafe and Nakata 2012] 15 [Hamari et al. 2014] 7 [Fogg 2002]
Number of theories, frameworks or models	83 [Michie et al. 2014b] 15 [Wiafe and Nakata 2012]

Table 2:1 Behaviour change patterns identified in the literature

This "theoretical gap" [Hekler et al. 2013] makes knowledge transfer between interventions difficult because it is not clear how and why a given intervention succeeds or fails [Nilsen 2015]. Under-use of theory is likely to impact the efficacy of the intervention, because important design characteristics are overlooked [Moller et al. 2017]. There is some evidence that interventions with a strong theoretical basis have a stronger association with efficacy [Webb et al. 2010b; Taylor et al. 2012], although this point is the subject of some debate [Michie and Prestwich 2010]. The shift to delivering behaviour change via technology is a key opportunity to deliver interventions based on systematic application of theory [Moller et al. 2017].

The gap in theory use reflects a lack of clarity around how to apply commonly-used theories to DBCIs. Health behaviour theories have been criticised for being "woefully underspecified" [Sheeran et al. 2017]. The inability of one single theory to address all aspects of behaviour change means researchers tend to use a "pick-and-mix" approach for strategies [Honka et al. 2011; Bandura 1998; Hekler et al. 2013]. For example, the myBehavior system incorporates elements from the Fogg Behavior Model, two decision theory models and Social Cognitive Theory [Rabbi et al. 2015], while Consolvo et al.'s set of design strategies incorporates strands from Cognitive Dissonance Theory [Festinger 1957] and the Transtheoretical Model [Prochaska and Velicer 1997], amongst others [Consolvo et al. 2009b].

In this pick-and-mix context, theory overlaps mean disagreement about which strategy belongs to which theory [Doshi et al. 2003]. This is a particular problem for DBCI designers wishing to target nonconscious behaviours because (a) it is not clear how the most commonly-used theories relate to such behaviours and (b) the theory is unclear, for example with no theoretical consensus on habit

mechanisms [Neal et al. 2006]. This chapter aims to clarify the ability of commonly-used theories to explain nonconscious behaviours, and to bring together the most pertinent theories and strategies into an explanatory model that can inform the design of DBCIs to target them.

THEORY SELECTION

We selected ten prominent theories in the literature and analysed their application to changing nonconscious behaviours. They either: directly address nonconscious behaviours (Behaviourism; Theory of Interpersonal Behaviour; Dual Process Theory; modern Habit Theory); are commonly used in behaviour change and DBCI research (Theory of Planned Behaviour; Social Cognitive Theory; Transtheoretical Model; Goal Setting Theory); directly address technology-mediated behaviour change (Fogg Behavior Model); or are comprehensive in their coverage (COM-B). To indicate the usage of these theories more widely we performed a search within the ACM Digital Library, Google Scholar and Scopus. Table 2:2 shows an overview of the current use of these theories through 1) the number of mentions in the ACM Digital Library within ACM Journals and Proceedings [2] (ACM search column); 2) the citations for the key papers relating to each specific theory (Google Scholar Citation and Scopus citations column). For theories with multiple sources (Behaviourism, Dual Process Theory, Social Cognitive Theory), we have selected one or two relevant sources as a reference point. Since mere mentions and citations do not necessarily reflect implementations, we augmented the results with recent applications of each theory from the DBCI research (Recent Implementations column) and the domain of application (Behaviours Targeted column). Modern Habit Theory is not listed in Table 2:2 because there is no one key paper that defines it.

This chapter does not aim to provide a comprehensive summary of all possible behaviour change theories and models available. Our aim is to consider the utility of applying the selected theories to changing nonconscious behaviours and DBCIs, and to highlight recent research using them.

[2] The search terms used were: theory/model title and (“behaviour change” or “behavior change” or “persuasive technology”

Theory/Model	*ACM search results*	*Google Scholar*	*Scopus*	*Citations based on*	*Summary*	*Key determinants of behaviour*	*Recent Implementations*	*Domains*
Transtheoretical Model	150	4942	2487	[Prochaska and Velicer 1997]	Six stages of behaviour, with ten processes for change. Interventions can move people between stages by targeting self-efficacy and perception of advantages and disadvantages of behaviour.	Individual stage of change; self-efficacy; decisional balance.	[Paay et al. 2015; Park and Gweon 2015; Wittekind et al. 2015; Southern et al. 2017]	Smoking; smartphone use; driving
Social Cognitive Theory	57	11673	2882	[Bandura 2001]	Behaviour is determined by an interaction between existing behaviours, the environment (including social factors), and personal cognitive, affective and biological influences.	Expected behavioural outcomes, environment and personal factors including self-efficacy.	[Rabbi et al. 2015; Khan et al. 2012]	Physical activity and diet; snacking
		264	-	[Bandura 1986]				
Theory of Planned Behaviour	56	50089	19954	[Ajzen 1991]	Behaviour is rational, determined by conscious intentions and Perceived Behavioural Control (an internal assessment of their ability to perform the behaviour).	Intention and Perceived Behavioural Control.	[Bexheti et al. 2015; Chen et al. 2014; Comber and Thieme 2013; Suh and Hsieh 2016]	Exercise; recycling; general behaviour change
Operant conditioning; behaviourism	45[a]	*10981	-	[Skinner 1938]	Behaviour is learned from interacting with the environment. This interaction forms stimulus-response associations.	External environment.	[Cowan et al. 2013; Kirman et al. 2010; Foster et al. 2011; Adams et al. 2009]	Environmentally friendly behaviours; exercise
Goal-setting theory	43	5258	2073	[Locke and Latham 2002]	Behaviour occurs where intentions are specified with an appropriate level of difficulty and specificity, and are accepted by users.	Intentions, contextual constraints.	[Konrad et al. 2015; Gouveia et al. 2015; Sleeper et al. 2015; Lomas et al. 2017]	Stress; physical activity; social network site behaviour; learning

a – 34 Operant conditioning results + 11 behaviourism results
** –theories that do not have one single article that defines them*
- items missing from Scopus

Theory/Model	*ACM search results*	*Google Scholar*	*Scopus*	*Citations based on*	*Summary*	*Key determinants of behaviour*	*Recent Implementations*	*Domains*
Fogg Behavior Model	8b	948	214	[Fogg 2009b]	Behaviour is executed when 3 elements co-occur: motivation, ability and a trigger.	Motivation, ability and a trigger.	[Rabbi et al. 2015; Oduor et al. 2014; Sleeper et al. 2015; Lee et al. 2017a]	Physical activity and diet; social influence; social network site behaviour.
Dual Process Theory	6c	*2960	1426	[Strack and Deutsch 2004]	Behaviour is determined by two distinct sets of cognitive processes: the Type 1 automatic system, formed of associative links; and the Type 2 conscious, deliberative system.	Interaction of two sets of cognitive processes: Type 1 processes (fast, automatic, nonconscious, associative); and Type 2 processes (slower, deliberative, conscious).	[Adams et al. 2015; Pinder et al. 2015a; Wang et al. 2014; Phelan et al. 2016]	Eating; privacy.
		13071	-	[Kahneman 2011]				
COM-B model	0[d]	1123	612	[Michie et al. 2011]	An interacting system of capability, opportunity and motivation.	Capability, opportunity and motivation.	[Lee et al. 2017a; Walsh et al. 2016]	Sleep; physical activity
Theory of Interpersonal Behaviour	0[d]	2085	-	[Triandis 1977]	Extends reasoned-action models by incorporating repeated past behaviour.	Past behaviour, intention and situational conditions.	[Moody and Siponen 2013; Gimpel et al. 2016]	Use of technology.

b plus 81 direct citations within ACM
c half of these papers were co-authored by Charlie Pinder
d search run 07/06/2017. All other ACM searches run 28/04/16. Google Scholar and Scopus searches run June 2017.
** theories that do not have one single article that defines them*
- items missing from Scopus

Table 2:2 Search results of theory/model mentions in the ACM plus citations and recent implementations

A key historical split in behaviour change theories and models is between behaviourism, which prioritises the role of the external environment in triggering behaviour, and cognitive theories, which argue that behaviour can also be explained by abstract cognitive constructs such as thoughts and motivations. More recently, integrated theories and models have emerged to reconcile both standpoints since neither theory can account for all the complexities of behaviour change [Prochaska and Velicer 1997; Bandura 1998]. We consider our ten theories and models in each of these three categories below before addressing their overlaps and omissions.

Behaviourism

Behaviourism is a key theory in understanding nonconscious behaviours because it focuses on the effects of the external environment on behaviour. It explicitly rejects the use of cognitive constructs to explain behaviour because they cannot be rigorous observed: only directly observable actions are considered.

Overview

Behaviourists see nonconscious behaviours as stimulus-response pairs formed outside conscious decision-making [West 2006] via two mechanisms of associative learning: classical and operant conditioning. A stimulus becomes associated with a particular response via repetition. Classical conditioning is the simple pairing of stimuli with responses; operant conditioning is the pairing of a stimulus-response with a positive or negative outcome. i.e. a reward for a wanted response, and a punishment for an unwanted one. Rewarding a behaviour increases stimulus-response links and makes it more likely to be repeated. With repetition over time, any contextual cues that co-occur with a behaviour can trigger it [Davis 2001]. A behaviour is considered habitual when removing the reward does not diminish the behaviour, i.e. it is resistant to *extinction*. For example, a smoker who initially felt a positive reward from smoking (operant conditioning) may be prompted to smoke by the sight of a cigarette packet (classical conditioning), regardless of subsequent reward.

A key determinant of the impact of operant conditioning is how reinforcement is delivered, the reinforcement schedule [Staddon and Cerutti 2003]. A variable reinforcement schedule, where a reward is delivered to an average time or response rate, not always at a given time or response, is more effective in producing behaviour that is resistant to extinction, compared to constant or random reinforcements [Bijou 1957].

Recent implementations and empirical evidence

Erev and Gopher argue that a reinforcement learning model – where the probability of a certain behaviour being performed increases when it is positively reinforced – provides "an extremely good approximation of behaviour in a wide set of situations" [Erev and Gopher 1999]. However, much research applying behaviourism in DBCIs is speculative. For example, Adams et al. suggest that pervasive exercise games are a good test-bed to explore behaviourist learning principles, but did not test this hypothesis [Adams et al. 2009].

Some researchers suggest that principles of operant conditioning and variable rewards underpin the use of social networks [Fogg 2009a], and the problematic use of both social networks [Andreassen 2015] and the internet in general [Davis 2001]. However, neither claim is yet supported by empirical evidence.

There is some evidence that positive reinforcement can impact on unwanted behaviours: a review of smoking cessation interventions during pregnancy found the most effective strategy was providing incentives [Lumley et al. 2009]. Positive reinforcements via virtual rewards are common in DBCIs, but as we discuss in the next chapter, this is not a panacea for motivating behaviour. A recent implementation of variable reinforcement found some evidence that operant conditioning can change and maintain more secure behaviour, although the sample sizes were small [Villamarín-Salomón and Brustoloni 2010].

Negative reinforcement or punishment strategies are relatively rare in DBCIs [Kirman et al. 2010; Orji and Moffatt 2016]. This may be due to ethical concerns [Fogg 2002] and fear of disengaging users [Consolvo et al. 2009b]. Nevertheless, there is evidence that aversive feedback does not necessarily deter users [Foster et al. 2011]. One wearable DBCI employing a punishment strategy is Pavlok, which allows users to trigger a mild electric shock to punish unwanted habitual behaviours [Pavlok 2015]. Similarly, researchers have implemented less painful punishment techniques, for example making interaction more tedious [Foster et al. 2011; Cowan et al. 2013], but none have been tested over the long term with a large user group.

Theoretical issues

Behaviourism is unable to explain higher-order behaviour involved in the formation of nonconscious behaviours such as goals and conscious expectations of outcome. Kihlstrom et al. argue that implicit

learning involves some cognitive abstract representation of the knowledge, above and beyond the simple behaviourist associations [Kihlstrom et al. 2007].

Cognitive theory

Given the limits of behaviourism, we now turn to a key cognitive theory of behaviour change, the Theory of Planned Behaviour, which peers into the 'black box' of cognitive representations of external and internal behavioural drives.

Theory of Planned Behaviour

Overview

The Theory of Planned Behaviour [Ajzen 1991] is a rational-action theory that specifies that intentions drive behaviour. A person's behaviour is determined by their conscious intention to perform that behaviour and their Perceived Behavioural Control, an internal assessment of their ability to perform the behaviour. This intention is itself determined by behavioural attitudes, perception of subjective norms relating to the behaviour and Perceived Behavioural Control [Ajzen 1991]. It is "the most extensively studied social cognition theory" [Hardeman et al. 2002].

Recent implementations and Empirical evidence

Schneider et al. applied the theory to explore motivations of 643 mobile fitness coach users, finding that attitude, subjective norm and Perceived Behavioural Control was a good predictor of intention, although levels varied across personality types [Schneider et al. 2016]. There is mixed evidence to support the theory from metareviews. Hardeman et al.'s review of 24 interventions found few studies actually using the theory, and a lack of evidence linking theory components to intervention outcomes. Webb & Sheeran's meta-analysis suggests intentions are insufficient to fully explain behaviour change, with "a medium-to-large change in intention … lead[ing] to a small-to-medium change in behaviour" [Webb and Sheeran 2006]. Crucially, an intention-behaviour gap persists, particularly in the presence of strong habits [Gardner et al. 2011; Webb et al. 2010b].

Theoretical issues

The Theory of Planned Behaviour is not a theory of behaviour *change*, and there is evidence that determinants of intention change over time [Suh and Hsieh 2016]. The theory thus has limited application to habitual behaviours since they only emerge in the presence of intentions enacted repeatedly in stable contexts. Sniehotta argues that the Theory of Planned Behaviour has major

conceptual flaws, including no testable descriptions of how to modify intentions and therefore behaviour [Sniehotta 2009]. The theory omits context, habits and emotions and other nonconscious possible determinants of behaviour [Jackson 2005; Schneider et al. 2016; Sniehotta et al. 2014]. The inability of the model to deal with the intention-behaviour gap in the presence of habits is particularly problematic: several studies show that changing intention tends to impact on behaviour only where habits are not involved [Triandis 1977; Webb and Sheeran 2006].

Integrated models

Integrated models try to provide more overarching models of behaviour. They address dissatisfaction with the polarised view from behaviourists, that individual behaviour is solely determined by the environment, and cognitivists, that behaviour is solely determined by internal cognitive factors [Bandura 1978].

Theory of Interpersonal Behaviour

Overview

The Theory of Interpersonal Behaviour [Triandis 1977] extends reasoned-action models by explicitly including habitual behaviour and the context. Habit (expressed as frequency of past behaviour) and behavioural intention interact with situational conditions to determine behaviour. More frequently enacted behaviour weakens the intention-behaviour relationship. Behavioural intentions are the product of attitudes, social factors and affect (the experience of emotion), with affect providing a largely nonconscious input into behavioural decision making. Thus the intention construct includes both nonconscious and conscious components.

Recent implementations and Empirical evidence

There have been relatively few implementations of the theory. The DBCIs based on it tend to focus on issues of technology acceptance. Moody & Siponen applied the theory to explore use of the Internet at work for non-work purposes, finding evidence to support the model's key assumption that intention and habits are both significant in predicting the target behaviour [Moody and Siponen 2013]. However, the research emphasised social factors in the workplace; it is not clear whether the results generalise to less social domains. Gimpel et al. found that habit was a predictor of intention to use smartphones [Gimpel et al. 2016], although neither habits nor smartphone behaviour were measured.

Theoretical issues

Low usage in DBCIs means it is difficult to establish efficacy. Low usage may be due to a lack of clarity over how to apply it to DBCIs. Further, using just "frequency of past behaviour" to approximate habits is insufficient. Danner et al. found evidence that past behaviour frequency only moderates the intention-behaviour relationship when information about context stability is also represented [Danner et al. 2008]. Although the Theory of Interpersonal Behaviour includes "facilitating conditions", it does not directly address the role of such conditions in forming habits – i.e. context stability. It may not therefore adequately capture habitual behaviour.

Social Cognitive Theory

Overview

Social Cognitive Theory [Bandura 2011; Bandura 1978] states that behaviour is determined by an interaction between existing behaviours, the environment, and personal cognitive, affective and biological influences. Social influence is a particularly important environmental factor. Social Cognitive Theory suggests that behaviour change arises from two sorts of belief: firstly that a given response will have a desired outcome, and secondly that the individual believes themselves capable of the response [Clark and Janevic 2014]. The theory predicts that desired behaviours are performed where environmental barriers are low and self-efficacy is high [Armitage and Conner 2000]. It also incorporates elements of behaviourism via the mechanism of reinforcement for learned behaviours.

Recent Implementations and Empirical Evidence

Implementations of Social Cognitive Theory tend to emphasise the construct of self-efficacy rather than testing the theory as a whole e.g. [Rabbi et al. 2015]. Some empirical evidence supports the interaction between self-efficacy and behaviour change: a meta-analysis of physical activity studies found 3 techniques "associated with [statistically] significant increases in both self-efficacy and physical activity behaviour; 'action planning', 'reinforcing effort or progress towards behaviour' and 'provide instruction'" [Olander et al. 2013]. Nevertheless, the overall effect was small, several other techniques had non-congruent effects on self-efficacy and physical activity, and the authors found that the reporting of intervention techniques was "inadequate" [Olander et al. 2013]. In addition, the identified techniques are consistent with Goal Setting Theory [Locke and Latham 2006], and behavioural theories of reinforcement, so it is not clear what additional contributions self-efficacy might provide, either at the theoretical or empirical level. Overall, Armitage & Conner argue that

Social Cognitive Theory-based interventions typically account for small- to medium- levels of variance in behaviour [2000].

Theoretical issues

Social Cognitive Theory has been criticised for failing to encompass habituation [Martin et al. 2014]. The implication is that habits are hard to change because they are perceived to be hard to change. Social Cognitive Theory relies on conscious, rational processing of behaviour change intentions and outcome expectancies, which do not reflect the observed automaticity of contexts triggering habitual behaviour. It suggests that self-management is the key to breaking habits [Bandura 1998], but it is not clear how individuals can deal with low levels of deliberative cognitive resources to perform self-monitoring and self-regulation. Further, although the model does include context as a behavioural determinant, the focus is on the impact of social pressures such as role models and social support. Again, this omits the phenomenon of habits ceding control of behaviour to contextual cues.

The Transtheoretical Model

Overview

The Transtheoretical Model [Prochaska and Velicer 1997]) or "stages of change" model was derived from a study of 872 people attempting to give up smoking on their own [Prochaska and DiClemente 1983]. The model identifies six states of health behaviour change, from pre-contemplation (not even considering changing behaviour) to actively modifying their behaviour and/or the environment, through to maintaining the new behaviour and possible relapse. The model also identifies a set of ten processes for change, each of which has a different suggested emphasis for any given stage [Prochaska and Velicer 1997]. Key drivers of movement between the stages are self-efficacy and decisional balance (weighing up pros and cons) [Prochaska and DiClemente 1983].

Recent Implementations and empirical evidence

The Transtheoretical Model has been used widely in health behaviour change [Marshall and Biddle 2001], and in DBCIs in general [Lin et al. 2006] and Table 2:2. Many implementations focus on the pre-contemplation stage, where participants require information about their behaviour to motivate change e.g. [Southern et al. 2017; Park and Gweon 2015]. Wittekind et al. used the model in an anti-smoking DBCI to measure participants' readiness to quit smoking, rather than to design an intervention [Wittekind et al. 2015].

There are reasons to doubt the model's efficacy. A metareview of smoking cessation interventions found no evidence for a statistically significant effect of interventions based on it [Jepson et al. 2006]. Aveyard et al. concluded that there was "no evidence that Transtheoretical Model-based interventions [are] effective" [Aveyard et al. 2009].

Theoretical issues

Bandura criticised the stages of change as "arbitrary pseudo-stages" rather than genuine stages [1998]. West lists several empirical challenges to the Transtheoretical Model [West 2005], and argues it should be discarded because of fundamental theoretical flaws. One key flaw in considering habits is that the Transtheoretical Model assumes that people make stable rational choices, rather than being subject to nonconscious influences.

COM-B model and the Behaviour Change Wheel

Overview

The COM-B model [Michie et al. 2011] emerged from research systematically reviewing and combining behaviour change theories and frameworks relating to health behaviours. The model states that behaviour is determined by an interacting system with three essential components: capability, opportunity and motivation. Together with the Behaviour Change Wheel [Michie et al. 2011; Michie et al. 2014a], it provides comprehensive guidelines for behaviour change researchers to plan interventions. It essentially formalises the pick-and-mix approach.

The COM-B model addresses some gaps in rational-action models such as the Theory of Planned Behaviour by including nonconscious components like "impulsivity, habit, self-control, associative learning and emotional processing". The model includes both automatic and analytical brain processes in the *motivation* concept, which encompasses all brain processes that "energize and direct behaviour" [Michie et al. 2011], and is derived from the PRIME model [West 2006]. *Opportunity* includes all factors external to an individual that "make the behaviour possible or prompt it", while *capability* includes all factors internal to an individual that contribute to their ability to perform a behaviour [Michie et al. 2011].

Empirical Evidence and Recent Implementations

Walsh et al. used the COM-B model and Behaviour Change Wheel to devise an app for physical activity over 5 weeks [Walsh et al. 2016]. Their intervention group, which featured feedback and

information about discrepancy between current behaviour and goal had showed a small-to medium statistically significant improvement over the control. Lee et al. recently employed the model in a context-aware sleep intervention [Lee et al. 2017a]. However, COM-B was combined with many other techniques and strategies (e.g. Fogg's Behaviour Model; goal setting theory; self-monitoring) and it is therefore difficult to make conclusions about the use of the model itself from their work.

Theoretical Issues

The COM-B model is relatively new and therefore relatively untested in HCI [Cibrian et al. 2016]. Since it and the Behaviour Change Wheel are explicitly positioned as practical design, rather than as explanatory theory, their application to nonconscious behaviours is unclear. Further research is required to determine whether they can improve intervention efficacy [Michie et al. 2011], particularly in DBCIs responsive to dynamic contexts and individual preferences [Michie et al. 2013b].

Fogg Behaviour Model

Several models specifically relate to technology-mediated interventions. For reasons of brevity, here we only outline Fogg's highly-cited research[3].

Overview

The Fogg Behavior Model [Fogg 2009b] focuses on computer-based persuasion [Fogg 2002]. It proposes three key determinants of behaviour: motivation, ability and a trigger. All elements must occur at the same time to generate a behaviour. Fogg also created: the Behavior Grid [Fogg 2009a], a taxonomy of 35 ways behaviour might change; the Behavior Wizard [Fogg and Hreha 2010] which attempts to merge the previous two items; and the 'Tiny Habits" model ([Fogg 2015], not yet published in a peer-reviewed form), which suggests DBCIs should change the performance context, break the required habitual behaviour into small steps, and reward small step completion.

Recent Implementations and empirical evidence

Establishing empirical evidence for the Fogg Behaviour Model is difficult because it is a process model rather than a theory. Researchers also tend to use it alongside other models, e.g. Cambo et al.'s work uses the Fogg Behavior Model with the Health Action Process Approach [Cambo et al.

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[3] 1,984 citations listed in the ACM Digital Library at June 2017, and see Table 2:2

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2017], which makes it difficult to draw conclusions about the model. Sugarman & Lank used the model to inform a qualitative survey of methods to encourage reduction in electricity consumption, although again they incorporated elements from other theories [Sugarman and Lank 2015].

Theoretical issues

Fogg's work is a behaviour change principles approach [Noar et al. 2008]. The Fogg Behaviour Model is a simple conceptualisation of behaviour with clear design implications: provide people with an appropriate trigger, motivation and ability to perform a wanted behaviour and it will occur. However, the underlying psychological mechanisms of change are less clear. Further, although Fogg sees the point of persuasive technology as "fundamentally about learning to automate behavior change" [Fogg 2009b], the Fogg Behavior Model has little to say about the automatic components of behaviour or routine behaviour [Oulasvirta et al. 2012]. Ferebee found ambiguities and a lack of guidelines in mapping existing interventions to the Behavior Grid [Ferebee 2010].

Discussion of competing models

Theory overlaps

Health behaviour change models contain many components, some of which are shared or overlap [Taylor et al. 2006]. For example, intentions are a key behavioural determinant in the Theory of Planned Behaviour, the Theory of Interpersonal Behaviour and Social Cognitive Theory, although the theories differ in the elements that determine that intention. The notion of "perceived behavioural control" from the Theory of Planned Behaviour is similar to parts of the Theory of Interpersonal Behaviour's notion of "facilitating conditions" and Social Cognitive Theory's concept of self-efficacy. Common to these models is the implicit assumption that users form intentions along rational, conscious lines. Most health behaviour theories assume that conscious attitudes and intentions, self-efficacy and social influences impact most on behaviour [Noar et al. 2008].

The Transtheoretical Model, the Fogg Behaviour Model and COM-B are *process* models [Nilsen 2015], which focus more on the process of designing behaviour change interventions rather than the theory. Process models may have greater utility to intervention designers than framework models [Rogers 2004]. However, process models may not always highlight the underlying theory: although the COM-B model is explicitly couched in the PRIME model of motivation, the Fogg models do not have explicit theoretical underpinnings.

There are also clear overlaps between the three-part models that address interactions between behaviour, the environment and internal cognitive factors (Fogg, COM-B, Theory of Interpersonal Behaviour and Social Cognitive Theory). Indeed, Lee et al. recently combined the Fogg Behavior Model and COM-B into a single approach which assumed a given behaviour occurred when "opportunity, ability, motivation, and a trigger all align" [Lee et al. 2017a].

Intentions & Motivations

A key common determinant of behaviour is intention. An intention is a decision to undertake a particular behaviour at a future point in time. It encompasses the person's motivation to perform the behaviour – the direction (to perform the behaviour or not) and the intensity (how much value they assign to that performance) [Sheeran 2002]. The Theory of Planned Behaviour, the Theory of Interpersonal Behaviour and Social Cognitive Theory all assume that intentions are key determinants of behaviour, and those intentions arise from the likelihood and desirability of the outcomes of a given behaviour [Deutsch and Strack 2010; Webb and Sheeran 2006]. However, it is not clear exactly how intentions drive behaviour [de Bruin et al. 2012], nor how the theories see any interaction between habit and intentions.

Motivation is a value attached to a particular intention. Motivation is a key construct in the Theory of Interpersonal Behaviour, Social Cognitive Theory, the COM-B model and the Fogg Behavior Model, and is central in moving people from contemplation to active stages in the Transtheoretical Model. We agree that DBCIs require people to be consciously motivated to change their behaviour to engage in interventions at the outset. However, most models (with the key exception of COM-B) focus on conscious, rational motivations, omitting important automatic aspects of motivation including the impact of contextual cues, internal physiological states (e.g. hunger) and emotions.

Theory gaps

Despite some consensus on behavioural determinants between the theories, there are gaps in their ability to drive the design of behaviour change interventions. Not all the models are dynamic, or specify how their constructs or the relationships between them change over time. This limits their application to DBCIs that can adapt rapidly to their users and changing inputs [Riley et al. 2011]. Some models omit the impact of the context, habit and/or emotions in determining behaviour.

Not all the theories explore how behaviour *changes* and there is little consensus on how to combine overlapping constructs to change behaviour [Noar et al. 2008]. For example, the Theory of Planned

Behaviour predicts behaviour, rather than addressing how intentions can change over time [Suh and Hsieh 2016].

The practical application of theories is not always clear. Despite intentions being a core construct in many behaviour change theories, they do not tend to address how those intentions are formed and how their relationship to behaviour may change over time. The exception is the Transtheoretical model, which explores *when* intentions change, but not *how* [Armitage and Conner 2000].

Many theories incorporate elements of behaviourist operant conditioning, e.g. positive reinforcement in the Transtheoretical Model and Social Cognitive Theory [Adams et al. 2017]. However, despite the crucial role the environment plays in behaviourism, many common theories emphasise individual/interpersonal variables rather than broader social/environmental variables [Davis et al. 2015b; Taylor et al. 2006]. This is a crucial omission in their application to understanding and changing habits given the role of contextual cues in triggering habits.

Nonconscious behaviours including habits are key constructs omitted from many behaviour theories, particularly health-related theories [Nilsen et al. 2012], despite compelling empirical support for the role of habit as a moderator of the intention-behaviour link [Webb and Sheeran 2006; Sheeran et al. 2017]. In general, models that assume a rational, deliberative process as a key determinant of behaviour (e.g. the Transtheoretical Model and the Theory of Planned Behaviour), are insufficient to explain the persistence of an "intention-behaviour gap" [Gardner et al. 2011; Webb et al. 2010b].

Theories that include habit either mention it somewhat in passing (COM-B model) or restrict its determinants too narrowly (e.g. behaviourism's failure to incorporate cognitive constructs that operate during habit formation). Even theories that explicitly incorporate habit e.g. the Theory of Interpersonal Behaviour and Social Cognitive Theory, fail to explain how and why habits operate, which limits their practical application. Further, although COM-B, the Theory of Interpersonal Behaviour and Social Cognitive theory all include elements of nonconscious motivation, it is not clear how the conscious and nonconscious elements work together to determine behaviour.

A good candidate for filling this theoretical gap in DBCIs is Dual Process Theory. Despite Dual Process Theory being the "probably one of the most significant theoretical developments in the history of social psychology" [Gawronski and Creighton 2006], it has been little used in DBCI interventions [Orji and Moffatt 2016; Webb et al. 2010a; Adams et al. 2015]. The under-use of Dual Process Theory is important because together with contemporary habit and goal theory, it directly addresses the

intention-behaviour gap and allows us to address the research gap in understanding how to build habit-focused DBCIs.

Bridging the theory gaps

This section outlines three theories that address the formation and stopping of nonconscious behaviours: Dual Process Theory, modern habit theory and Goal Setting Theory. Bringing these theories together can bridge the research gap in understanding how to change nonconscious behaviours using technology and therefore move to close the intention-behaviour gap. Dual Process Theory allows us to see how conscious and nonconscious forces interact to determine behaviour; modern habit theory indicates how these might combine to determine habitual behaviour; and Goal Setting Theory informs effective goal-setting strategies to help drive habit and nonconscious goal operation through behavioural repetition.

Dual Process Theory

Overview

Dual Process Theory contends that behavioural decisions arise from two distinct sets of processes: Type 1 (broadly automatic, e.g. habits) and Type 2 (broadly conscious, e.g. behavioural intentions). Type 1 processes are nonconscious cue-driven, heuristic, impulsive, associative, contextual, automatic, parallel processes that operate at speed; while Type 2 processes are conscious goal-directed, slower, rational, considered, rule-based, abstract serial processes [Evans 2011; Evans and Frankish 2009]. This split roughly maps onto the behaviourist/cognitivist rationalist divide, with habits forming part of the Type 1 set. Not all the nonconscious behaviours triggered by Type 1 processes are habitual [Marteau et al. 2012]. People may act in line with an impulse in response to a cue or in line with nonconscious goals without the action becoming a stable, repeated behaviour (see Chapter 7).

The crucial difference between behaviourism and Dual Process Theory is that in the latter, automatic behaviours rest on cognitive constructs, and thus may be altered using both cognitive and behavioural techniques. Dual Process Theory thus unites the behaviourist-cognitivist divide: behaviour is the outcome of an interplay between both Type 1 and Type 2 processes.

We have outlined common assumptions of Dual Process Theory, but there is no one definitive version [Evans 2008]. Rather, it is a family of theories from multiple fields of research [Stanovich

2011], including the CEOS model [Borland 2013], the Reflective-Impulsive model [Strack and Deutsch 2014] and System 1-System 2 theory [Kahneman 2011].

Recent Implementations & Empirical Evidence

Few DBCIs currently use Dual Process Theories [Adams et al. 2015]. A review of 85 DBCIs since 2000 found zero implementations [Orji and Moffatt 2016], although pilots are emerging, for example Adams et al.'s studies in "mindless computing" [Adams et al. 2015]. Phelan et al. applied the theory in a qualitative investigation into privacy behaviour, finding that the dual process view helps to inform the "privacy paradox" where privacy behaviour is inconsistent with privacy concerns [Phelan et al. 2016].

Behaviour change research as a whole has recently begun to advocate the targeting of Type 1 processes alongside Type 2 approaches [Bargh and Morsella 2010; Dolan et al. 2012; Marteau et al. 2012; Sheeran et al. 2013]. Dual Process Theories are being used increasingly in health behaviour interventions [Hofmann et al. 2008], e.g. Kremers et al. used Dual Process Theory to build a framework exploring the impact of environmental factors on weight gain [Kremers et al. 2006].

Neuroscientific evidence supports Dual Process Theory by showing that action-outcome behaviour (cognitivist goal-directed behaviour) and context-response behaviour (behaviourist habits) are associated with two different sets of brain processes [Gasbarri et al. 2014; Graybiel 2008; Yin and Knowlton 2006]. Presseau et al. measured deliberative and automatic predictors for six different healthcare behaviours (e.g. providing weight advice; prescribing for diabetes) using questionnaires and found that both predictors predicted behaviour [Presseau et al. 2014].

Theoretical issues

Since Dual Process theories are still little-used in DBCIs, it is difficult to establish their efficacy. Implementing Dual Process Theory is not trivial: there are multiple versions, and researchers are still actively developing the theory as it applies to behaviour change [Wiers et al. 2013; Borland 2016].

Nevertheless, Dual Process Theories agree on two key predictions: behaviour is an outcome of both Type 1 and Type 2 processes; and Type 1 processes (including habits) will dominate when Type 2 resources are depleted, during distraction, high cognitive load, time pressure, adverse mood and low self-control [Hofmann et al. 2008; Muraven and Baumeister 2000]. The relative importance of Type 1 and Type 2 processes as a determinant of behaviour also varies with personality [Sladek et al. 2006].

Thus the influence of Type 1 and Type 2 processes on an individual's behaviour will vary both over time and in comparison with other people.

Dual Process Theory does not in itself provide a practical framework of devising interventions to alter automatic behaviours. For this we need to examine two additional theories: modern habit theory and Goal Setting Theory.

Modern habit theory

Overview

Modern habit theory also integrates both stimulus-response behaviourist theories and goal-directed cognitive reasoned-action theories (e.g. [Wit and Dickinson 2009]). We have outlined the key points and some empirical evidence for the existence of habits above. This section therefore addresses recent implementations and some theoretical issues.

Recent Implementations

Stawarz *et al.* investigated the formation of habits in-the-wild, focusing on the relatively simple behaviour of participants reporting what they had for lunch [2015]. In a 4-week study, they found that automaticity was hindered both by smartphone reminders and positive reinforcement. Automaticity developed faster for participants depending on specific *if-cue then-behaviour* plans (Implementation Intentions), compared to reminders and reinforcement, but they found no significant differences to a control no-cues group.

Theoretical issues

Habit research is ongoing across multiple fields, with ongoing challenges in determining the exact mechanisms underlying habit formation [Tobias 2009; Yin and Knowlton 2006] and in studying its automaticity [Gasbarri et al. 2014]. Nilsen *et al.* suggest that there is a lack of empirical evidence supporting interventions based on habit theory [Nilsen et al. 2012].

Goal Setting Theory

Outline

Goal Setting Theory [Locke and Latham 2002; Locke and Latham 1990] explicitly explores how best to form goals to drive behavioural repetition when Type 2 processes predominate. It fills the theoretical gap in detailing how to specify intentions. The theory proposes that goals must be accepted by users

to be effective, that feedback on goal progress is important, and that two key aspects of goal setting determines their efficacy: difficulty and specificity. Hard, specific goals are more effective than easy, vague ones. Contextual constraints are considered a moderator [Latham et al. 2017]. Research is also moving towards incorporating the operation of nonconscious goals [Latham et al. 2017], which we address in Chapters 3, 6 and 7.

Recent implementations

DBCIs often used Goal Setting Theory alongside other theories. For example, Ding *et al.* used goal setting theory predictions within a context-aware walking app based on the Fogg Behavior Model [2016]. They found some qualitative evidence that users liked short-term step goals rather than daily or weekly goals, but it is unclear whether the results can be generalised.

Empirical evidence

Meta-analysis indicates that specific, difficult goals improved performance compared to asking people to "do your best", with effect sizes from .42 to .80 [Locke and Latham 1990], cited in [Locke and Latham 2002]. However, there is evidence that who assigns the goal makes a difference: when the DBCI sets the goals, easier goals may be more effective. Lomas et al. found that when self-selected, moderately difficult tasks were most motivating, but when externally assigned, easiest games were most motivating [Lomas et al. 2017]. Konrad et al. found evidence that adaptive, easy goals set by user's technology were more motivating than difficult goals [2015].

Theoretical issues

The two main theoretical issues with Goal Setting Theory is a lack of consensus on measuring goal commitment [Hollenbeck et al. 1989] and goal difficulty, and that research into nonconscious goals is at an early stage.

Summary

We have explored theoretical approaches to changing nonconscious behaviours. Three theories are good contenders to fill the theoretical gap in explaining nonconscious behaviour: Dual Process Theory, modern habit theory and Goal Setting Theory. We bring them together in a conceptual framework, the Behaviour Alteration Framework, in the next chapter to ease interpretation of how they combine to address nonconscious behaviours.

3. BEHAVIOUR ALTERATION FRAMEWORK

This chapter:

- introduces the Behaviour Alteration Framework (BAF)
- outlines how it helps to illustrate the influence of nonconscious processes on behaviour
- explores related strategies for NDBCIs.

OVERVIEW

The previous chapter identified gaps in the behaviour change research's ability to deal with automatic behaviours. This chapter outlines our suggested solution: a Behaviour Alteration Framework (BAF) that brings together Dual Process Theory, modern habit theory and Goal Setting Theory to understand how behaviour emanates from both conscious and nonconscious sources. We use the framework to explore potential avenues for interventions to change behaviour, and frame current HCI research within it.

INTRODUCTION

The BAF is a practical, illustrative framework that synthesises Dual Process Theory, modern habit theory and Goal Setting Theory so they can be applied more easily to DBCIs, including NDBCIs. The BAF provides a conceptual, theory-driven simplification of how external and internal factors combine to generate both automatic and deliberative behaviour. It answers a call for a practical tool to describe and assess NDBCIs [Hollands et al. 2016; Aarts et al. 1997]. It allows researchers to devise new interventions that do not solely rely on limited deliberative cognitive resources.

The BAF is shown in Figure 3.1. Behaviour is a function of:

(1) the context consisting of a set of cues;

(2) Type 1 associative processes generating behavioural impulses in response to cues;

(3) Type 2 deliberative processes generating explicit intentions; and

(4) individual differences (e.g. impulsivity), which determine the relative impact of Type 1 and Type 2 processes on behaviour.

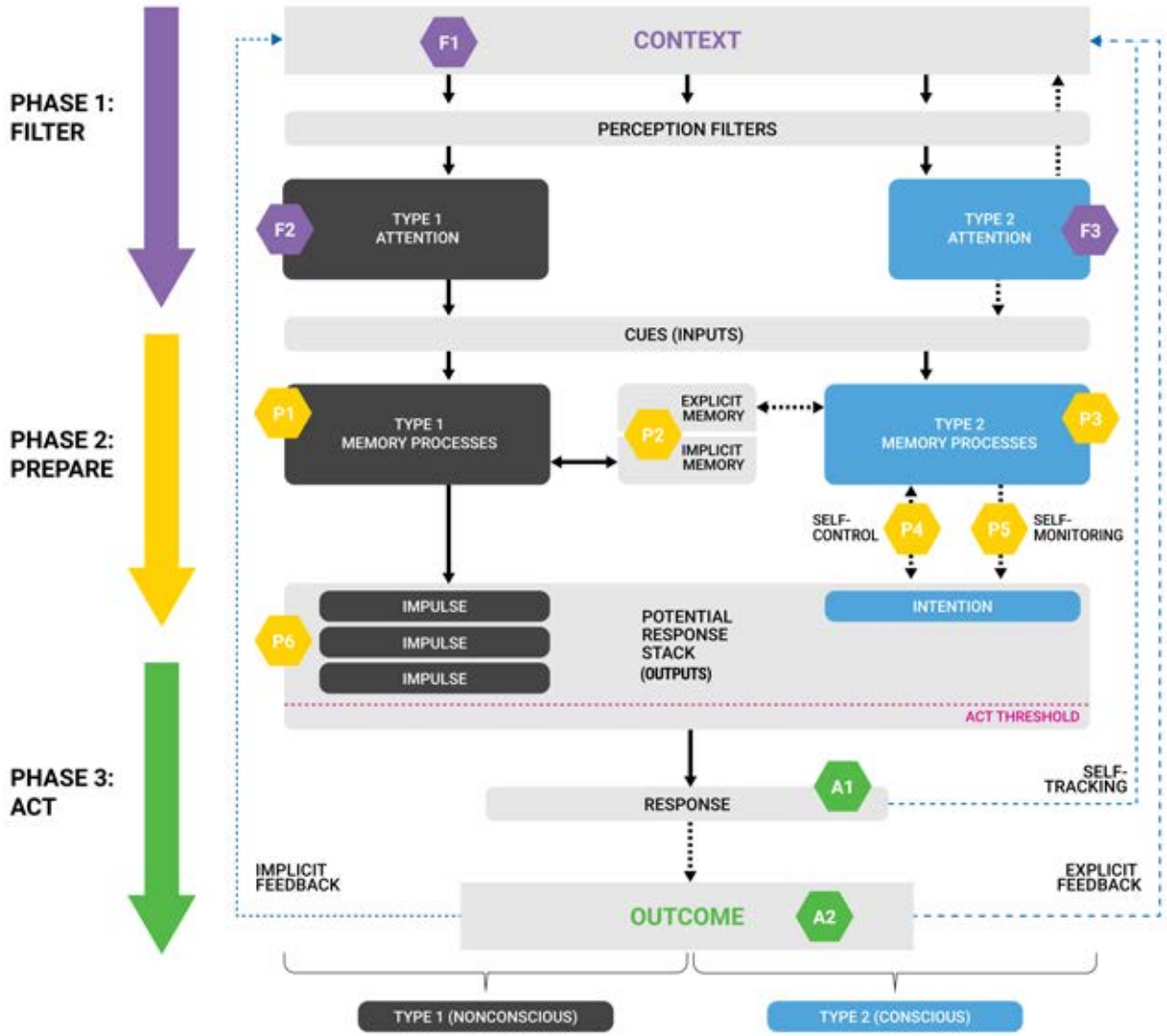


Figure 3.1 Behaviour Alteration Framework diagram

Solid lines indicate processes that always run; dashed lines indicate optional processes.

Context cues (F1) are filtered by both Type 1 (F2) and Type 2 (F3) attentional processes to form a set of inputs to subsequent memory processes of Type 1 (P1) and Type 2 (P3).

Competing drivers to act populate the potential response stack (P6). These may be consciously noticed by self-monitoring (P5) and overridden by self-control (P4).

The resulting behavioural response (A1) and (optional) outcome (A2) feed back into both Type 1 and Type 2 processes.

The framework is dynamic: at the *Filter* stage, cues flow through perception and Type 1 and Type 2 attention filters to create an input set. At the *Prepare* stage, Type 1 and Type 2 memory processes match these cues to potential responses, Type 1 impulses or Type 2 intentions. These compete to become a single response at the *Act* stage. Information from observed response and outcomes feed back into both Type 1 and Type 2 processes. Solid lines indicate processes that run continuously; dashed lines indicate processes that may run. Note that the BAF is not intended to represent the various highly complex physical architectures that operate in the brain. Instead, it is a virtual conceptual architecture, where boundaries between systems need not be rigid [Sloman 2002].

With sufficient repetition of simple behaviours in stable contexts, cycles around the Filter-Prepare-Act stages become more automatic. The corresponding context-response behaviour links become stronger and proceed faster, with decreasing need for conscious attention. People's behaviour then transfers from slower Type 2 to faster Type 1 processes, from the conscious right-hand side of Figure 3.1 to the nonconscious left hand side. Behaviour disruption strategies aim to call on Type 2 deliberation to override automatic Type 1 processes. Although disruption can be employed to a user's advantage, e.g. in error checking or reducing technology over-use [Cox et al. 2016], disruption also makes behavioural outcomes less stable because its success depends in part on available cognitive resources.

Dual Process Theory predicts that behaviour is the result of the simultaneous influence of Type 1 and Type 2 processes [Kremers et al. 2006; Presseau et al. 2014]. Automatic impulses to respond in a particular way, triggered by a given context, compete with other impulses and with intentions from Type 2 processes to determine a response [Gardner 2015]. The dominant response is determined by the relative strength of the items on the Potential Response stack, and is influenced by cognitive resources and an individual's cognitive capacity and processing style [Sladek et al. 2006].

Next we detail how automatic behaviours such as habits and nonconscious goal-directed behaviour are triggered and formed within the BAF.

Automatic behaviour trigger process

Filter

We start with a set of cues that make up a given context (F1). Cues include external features of the environment e.g. physical locations and other people, and internal features e.g. mood or physiological drives such as hunger [Wood et al. 2014]. This broad set of cues is first "filtered" by perception processes. Then they are filtered via Type 1 implicit attention processes (F2) and, optionally, Type 2 explicit attention processes (F3). Type 1 implicit attention filtration is influenced by mood, attitudes and stereotypes: some cues receive preferential implicit attention over others [Deutsch and Strack 2010]. Type 2 processes may use directed attention (F3) to select specific cues from the context. This directed attention has limited cognitive resources, so its ability to select cues is impacted by cognitive load. The result of the attentional filter process is a subset of cues as inputs to the potential response generation process, Prepare.

Prepare

Cue inputs are used by both Type 1 and Type 2 memory processes to generate behavioural schemas for action [Strack and Deutsch 2014]. Type 1 processes (P1) generate impulses from implicit memory while Type 2 processes (P3) generate intentions from explicit memory. These separate schemas compete to become enacted behaviour, via a mechanism to integrate parallel inputs into a single behavioural outcome [Bargh and Morsella 2010], the Potential Behavioural stack (P6).

Type 1 memory processes are fast, modular and parallel, so multiple impulses may be generated from input cues and placed on the Potential Response stack. These impulses include habits and automatic goal impulses. Habits are context-response impulses for behaviour that has been repeated in a stable context. Automatic goal impulses are *goal*-response links, allowing for nonconscious goal-driven behaviour when a goal acts as a cue [Aarts and Dijksterhuis 2000]. Impulses emerging from Type 1 memory processes may also be of a simple approach or avoid type [Keatley et al. 2013], for example instinctive behaviour to flinch from a loud sound.

The Potential Response stack (P6) may also contain conscious, deliberative intentions arising from Type 2 processes (P3). These may arise from explicit goals via the mechanism of self-control (P4). Intentions that have been set using Goal Setting Theory are assumed to take priority on the stack. Intentions include the intention not to act, i.e. impulse stifling, in the case that self-monitoring (P5) indicates an unwanted impulse is likely to be enacted. This ability requires that the Potential Response stack is to a certain extent accessible to conscious thought [Bargh and Morsella 2010].

The order of impulses and intentions in the Potential Response stack is determined by several factors: match with the particular cue [Norman and Shallice 1986]; affect towards the cue and/or response [West 2006]; and accessibility [Kahneman 2003; Danner et al. 2008]. Placing value on degree of 'match' means that behaviour enacted more often appears higher on the stack than less previously-enacted behaviour, since the match with a particular cue will be stronger. Thus an impulse to perform a behaviour that has been repeated in a stable context will appear higher in the Potential Response stack: these are automatic behaviours such as habits.

Act

A competitive winner-takes-all process determines which single behaviour is performed from competing schemas on the Potential Response stack [Hofmann et al. 2009]. Any potential response (impulse or intention) that exceeds a certain act threshold (the red dashed line in P6 in Figure 3.1) will be enacted if there are no rival potential responses [Wood et al. 2014]. Where competing potential responses cross the act threshold, arbitration using Type 2 processes is required.

A response may be followed by an outcome, a corresponding change in the environment or a reward. Information on the response and outcome feed back into implicit and explicit memory processes and therefore may impact on subsequent Act phases [Sun et al. 2005; Wood and Neal 2007].

Act arbitration process

Table 3:1 shows the different possible states of the Potential Response stack with respect to the act threshold (the red dotted line), and the behavioural response. Impulse A, impulse B and impulse C are impulses to perform behaviours A, B and C respectively; intention D is an intention to perform

behaviour D. The relative value of items on the Potential Response stack is indicated by position: the higher in the stack, the higher the relative value.

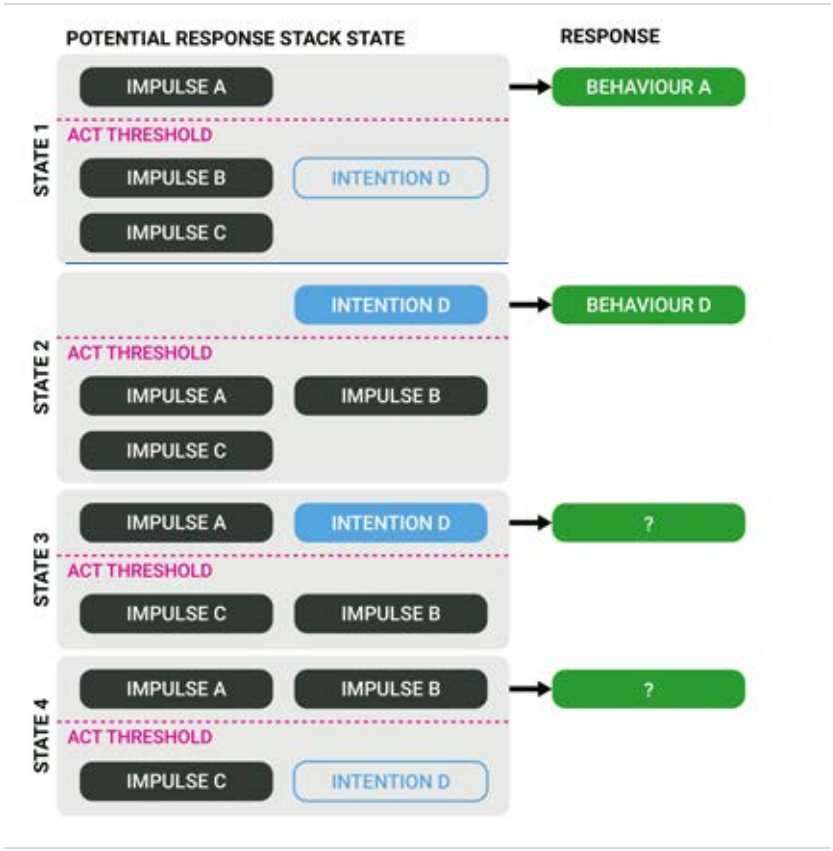


Table 3:1 Arbitration between competing Potential Responses

State 1 shows that where a single impulse crosses the act threshold, the impulse will be enacted regardless of intention: intention D is shown with a dashed outline to indicate that it may or may not be present. State 2 shows that where a single intention is strongly-held such that it alone crosses the act threshold (state 2), its target behaviour will be enacted regardless of competing, weaker impulses. State 3 shows that where conflicts between a Type 1 impulses and a Type 2 intention occur with similar implicit values so that both cross the act threshold, Type 2 processes may be alerted to arbitrate [Wood and Neal 2007]. State 4 shows that arbitration may also be alerted to differentiate between competing impulses.

Arbitration is the implicit core of many strategies to alter default automatic behaviours, e.g. to break habits. These strategies try to populate the Potential Response stack with conscious Type 2 intentions to compete with unwanted other potential responses in order to trigger deliberative arbitration. However, calling on Type 2 arbitration resources imposes cognitive load, which is not always available. Where arbitration cannot be performed, the most likely response is the highest-value impulse in the stack. Arbitration is hampered by multiple load factors including other Type 2 processes, ego depletion, time pressure, and individual factors including working memory capacity and low trait self-control [Hofmann et al. 2009]. This explains why many effortful intentions to change behaviour fail: when Type 2 cognitive resources are low, default Type 1 impulses predominate [Hofmann et al. 2009].

In case 3, if cognitively costly arbitration cannot be carried out, impulse A will predominate because impulses appear more quickly in the Potential Response stack in excess of the act threshold than slower intentions. Where impulse A represents any Type 1 automatic behaviour, generated by repeating a simple behaviour in response to stable contextual cues, such impulses will predominate when cognitive resources are low.

Automatic behaviour formation process

How might people form automatic behaviours, so that their default behaviour is congruent with their conscious intentions? Repetition is key. Habit formation requires that a given response (Act stage) is repeated in a stable context, i.e. with a stable set of cues arising from the Filter stage. With repetition, the impulse to perform the given response emerges as highest in the Potential Response stack (Prepare stage), triggered by the stable cues. The response (Act stage) may then proceed without conscious attention, i.e. the intervention of Type 2 processes. In behaviourist terms, stimulus-response links have been established.

This automatic behaviour formation process can be accelerated by rewarding the required response, i.e. operant conditioning, providing a rewarding outcome (A2). Rewards can promote the learning of context-response links [Wood et al. 2014]. A reward does not have to be explicit for an automatic behaviour to form. For example, Conroy et al. found evidence for an habitual element in sedentary

behaviour despite this behaviour not being explicitly rewarded or even consciously intended [Conroy et al. 2013].

The key task for DBCIs to form automatic behaviours is to foster behavioural repetition in a stable context. Traditional behaviour change interventions for forming new automatic behaviours is to use conscious Type 2 processes (the right-hand side of Figure 3.1) to drive repetition via mechanisms of reminders and self-control. However, as we outline below, the BAF also allows this repetition to be targeted via nonconscious Type 1 means.

Opportunities for DBCIs to intervene

This section discusses the opportunites our framework identifies to intervene to change behaviour. We cover both the cessation of persistent unwanted behaviours, and the creation of new persistent automatic behaviours; some techniques are appropriate for both. For behaviour-forming techniques, the key question is how to move from Type 2 to Type 1 processes, from right to left in Figure 3.1. This is a movement from behaviour arising from slow, limited, serial, explicit systems to behaviour arising from faster, parallel implicit systems. For behaviour-breaking techniques, the key question is how to alter existing Type 1 processes without relying on cognitively effortful disruptive Type 2 resources. Points of intervention are denoted by numbers F1-F3, P1-P6 and A1-A2 in Figure 3.1.

Filter: target the Context (Phase 1)

Removing or avoiding a cue that forms part of a cue-response link in an unwanted automatic behaviour will mean the undesired response is not initiated or performed. This approach is challenging because Type 1 associative links are not available to introspection [Neal et al. 2012; Orbell and Verplanken 2015]. People are unlikely to be aware of which cues are relevant to their unwanted automatic behaviours. An alternative strategy is to introduce cues to trigger required responses.

Alter context (F1)

OUTLINE

Adding or removing cues affects which impulses and intentions arise in the Potential Response stack. Changing cue properties such as ambience and size and/or placement, e.g. proximity and availability can also affect the stack [Hollands et al. 2013]. Context alteration is suggested as particularly applicable in the unhealthy eating domain [Wansink and Chandon 2014].

EVIDENCE

The primary implementations of context-altering DBCIs are ambient persuasive technologies, designed to change behaviour and/or attitude unobtrusively without requiring focal attention [Ham et al. 2009]. Examples include altering a workspace to encourage people towards the stairs [Rogers et al. 2010] and augmenting shopping trollies to influence consumer behaviour [Kalnikaite et al. 2011]. However, specific context-altering strategies lack a strong evidence base [Hollands et al. 2013].

Altering moods is also a context-alteration strategy. There is some evidence that mood-altering interventions can be successfully ported from psychology labs onto smartphones [Meinlschmidt et al. 2016], although the technique has yet to be applied in DBCIs.

CHALLENGES

Determining which cues to alter is difficult. Kremers et al. identified 35 broad environmental changes to promote change in food and activity behaviours [2012], and the individual efficacy of these changes remains unclear. Detecting appropriate emotional cues for a given behaviour is particularly difficult. Large-scale ambient persuasive interventions can have high installation costs. This cost drawback has triggered research into altering “micro-environments”, contexts on a smaller scale, e.g. product labelling or design [Hollands et al. 2013].

An alternative context-alerting strategy is to use pervasive technology e.g. smartphones to deliver cues, i.e. priming.

Priming (F1, P1, P6)

Type 1 processes include associative memory links between cues and affective and behavioural responses [Strack and Deutsch 2014]. They can be activated using priming, the unobtrusive presentation of cues to activate relevant mental representations [Shalev and Bargh 2011]. Priming can increase accessibility of a goal concept [Kahneman 2003], making it more likely to be performed [Bargh et al. 2001]. Positive valence towards a concept can also increase its accessibility [Kahneman 2003; West 2006], providing opportunities for affective priming [Custers and Aarts 2007]. In the BAF, priming is providing a specific cue within the context (F1) that crosses the attention barrier to form an input to Type 1 Prepare processes (P1). These processes select a target impulse from memory. Ideally, this impulse is relatively high on the Potential Response stack (P6) and therefore likely be enacted. If enacted and repeated in a stable context, it will become a habitual behaviour [Wood and Neal 2007].

DBCIs may implement two forms of priming behaviour: the activation of instinctive paths to achieve certain behaviour, or the activation of learned constructs such as goals.

INSTINCTIVE PATHS

OUTLINE

Several 'instinctive' context-response paths already exist. Stanovich argues these fast "genetic goals" are more easily primed than learned goals, and are more universal [2005]. Evidence of these instinctive paths include the influence of auditory [Spence and Shankar 2010] or other environmental cues [Wansink 2010] on eating behaviour, and suggesting apparent monitoring by displaying images of eyes increasing compliance with honesty boxes [Bateson et al. 2006]. The latter example implies the possibility that DBCIs merely appearing to monitor may increase compliance to behavioural norms.

EVIDENCE

Several pervasive systems have implemented instinctive triggers, particularly in the fitness domain. Several sound-based DBCIs react to user heartrate by selecting [Nirjon et al. 2012], altering [Oliver and Flores-Mangas 2006] or auto-generating workout music [Bauer and Waldner 2013], while the Zombies, Run! [zombiesrungame 2015] app exploits a 'flight from fear' hard-wired instinct to cue users to run faster using sounds of ravening zombie hordes. A sight-based intervention, in the healthy eating domain,

is the Mindless Plate. This prototype explored whether perceptions of food portion size could be altered using coloured plates, with somewhat encouraging short-term results [Adams et al. 2015].

An alternative 'instinctive' path is that of social priming (e.g. [Aharony et al. 2011]): humans are predisposed to react to the cue of seeing another person perform a behaviour by responding with similar behaviour. This theory is supported by some research in neuroscience [Kessler et al. 2006], but evidence for efficacy is mixed [Froehlich et al. 2010]. Instinctive primes are a good candidate for research where deliberative strategies have repeatedly failed, e.g. in the healthy eating domain [Wansink 2010; Obrist et al. 2014; Pels et al. 2014].

CHALLENGES

The key challenge is to identify the correct prime for a given behaviour. Once identified, the prime needs to be delivered in a sufficiently salient manner to cross the implicit and/or explicit attention filters (F2, F3). If the primed behaviour is not repeated in a stable context, no habit will be formed. This is not just an issue of context detection, since enacting the desired behaviour is not guaranteed, given differences in individual responses and concurrent different states of the Potential Response stack (P6). Further research is required to determine how best to deliver the instinctive prime so the related impulse appears at the top of the Potential Response stack, and is therefore likely to be enacted. The technique is likely to be most successful to direct people during situations of high cognitive load (e.g. driving, travelling) where arbitration is not possible.

NONCONSCIOUS GOALS

OUTLINE

To what extent can we prime learned associations, such as goal constructs, i.e. an association between a goal and the behaviour required to achieve the goal [Danner et al. 2011], to drive the formation of automatic behaviours? This strategy may mitigate some of the challenges in identifying and delivering instinctive cues. Modern goal research indicates that goals, instead of definitively forming part of conscious deliberation in Type 2 processes, can be both *activated* nonconsciously [Stajkovic et al. 2006; Aarts et al. 2008], and *operate* nonconsciously [Chartrand and Bargh 1996; Pessiglione et al. 2007; Förster et al. 2007]. Priming goals results in more persistent accessibility of the related concepts than

simply priming behaviour alone, at least until the goal-related behaviour is enacted [Bargh and Morsella 2010]. Primed impulses will therefore have more value in the Potential Response Stack (P6).

EVIDENCE

Chen et al. found some evidence in a single session pilot that priming intentions increased user engagement in an exergame [Chen et al. 2014], while Custers & Arts showed that goal priming increased both accessibility and affective valence and impacted on effort to pursue a goal [2007]. Priming can also be delivered nonconsciously, e.g. subliminally. Caraban et al. applied subliminal priming in a browser plug-in by decreasing the opacity of key words and found some evidence of priming on subsequent item selection [2017]. Evidence for the efficacy of goal priming as a behaviour change technique is mixed, supported by some [Sheeran et al. 2013; Sheeran et al. 2017], while other research is ambivalent [Wood and Neal 2007].

CHALLENGES

Goal priming requires work with users ahead of intervention to instil the goal along Goal Setting Theory lines so that it can be primed. Priming with no pre-training implicitly assumes that participants already associate the prime with the goal. Primes need to be designed carefully to avoid ironic effects where instructions such as “do not X” primes behaviour X [Earp et al. 2013]. There are some theoretical objections: Papies, in line with the COM-B model, argues that goal priming procedures can only be successful where individuals also hold sufficient motivation, capability and knowledge to pursue it [Papies 2016].

Nonconscious goal priming experiments in psychology frequently use supraliminal tasks where the aim of the task is concealed – e.g. by tasking users with a word search where the target words relate to the goal of 'performing well' [Bargh et al. 2001]. However, word search or scrambled sentence tasks are difficult interventions for DBCIs using pervasive computing technology, particularly using small-screened or unobtrusive technology. Subliminal priming provides a possible alternative method of prompting nonconscious behaviour. Subliminal priming can help to avoid user irritation [Ham and Midden 2010], be less likely than conscious prompts to promote behaviour in contrast with the goal [Glaser and Kihlstrom 2005], and ensure authenticity in response [Shalev and Bargh 2011].

Priming activation is distinct from habit activation. A habit is a learned context-response link, while priming activates multiple mental concepts in memory related to the prime [Wood et al. 2014]. To prime habit formation, DBCIs either need to be sufficiently context-aware to prime only within a stable context (to form new habits) or accept that their intervention may need to be persistent if stable-context-priming is not possible. The latter technological dependency may not lead to long-term behaviour change if the technology is abandoned [Renfree et al. 2016].

Alter cue salience (F2, F3)

OUTLINE

The likelihood that a given cue gets through the implicit perception filter is determined by its salience. Thus, a behaviour change strategy is to reduce the salience of contextual cues for unwanted responses, whilst increasing the salience of cues for wanted responses, using Cognitive Bias Modification (CBM) techniques for attention biases [MacLeod et al. 2009], CBM-A. An attention bias is the tendency for a given cue to receive disproportionate implicit and/or explicit attention, points F2 and F3 in Figure 3.1 respectively. Reducing attention for unwanted cues reduces the resulting unwanted response because the cue is less likely to become an input to Type 1 and Type 2 memory processes, and likewise the reverse with wanted cues.

EVIDENCE

Biases affecting attention can be altered by appropriate training [Hertel and Mathews 2011]. Evidence from psychology labs is encouraging, e.g. in the healthy eating domain [Kakoschke et al. 2014]. However, there are relatively few DBCI implementations, with most at pilot stages. One randomised controlled trial porting CBM-A techniques onto smartphones found inconsistent results with only small effects on attention bias scores [Enock et al. 2014].

CHALLENGES

CBM techniques face challenges in identifying relevant cues that need increasing/decreasing in salience, and in ensuring longevity of newly-learned responses [Hertel and Mathews 2011]. Mixed empirical

evidence indicates that additional research is required to determine how best to apply this strategy in DBCIs. We address this in Chapter 5.

Prepare: target the context-response link (Phase 2)

Train context-response (P1, P6)

OUTLINE

Cognitive Bias Modification for approach biases, CBM-Ap, trains context-response links. An approach bias exists when an individual has a default impulse towards an unwanted cue, i.e. a Type 1 Prepare processes, P1 in Figure 3.1. For example, a smoker may have an approach impulse towards a cigarette. CBM-Ap techniques train individuals to inhibit responses or reject these unwanted items, and to accept alternative wanted items. For example, the smoker might be trained to reject cigarettes and accept chewing gum.

EVIDENCE

Two CBM-Ap studies found small statistically significant results following brief training with challenging participants and long follow-up periods. Wiers et al. trained alcoholics with 4x15 minutes lab training sessions [2011]. Participants used a joystick to push away images of alcoholic drinks, and pulled towards them images of non-alcoholic drinks. The training altered the intervention group's small approach bias for alcohol to a strong avoidance bias, reflected in marginally statistically significant differences in relapse rates. Wittekind et al. trained psychiatric inpatients with a similar anti-smoking CBM-Ap over 4 sessions and found small statistically significant differences in self-reported nicotine consumption at 3-month follow-up [2015].

CHALLENGES

As with CBM-A, it is not clear how best to translate CBM-Ap to DBCIs. Cue identification may also be an issue, although it is easier for people to identify unwanted approach biases than unwanted attention biases. The behavioural impact of the two CBM-Ap studies was small, and intervention groups also received standardised Type 2 interventions (e.g. motivational interviewing). Nevertheless, evidence of impact of the minimal Type 1 training indicates potential in using more pervasive technology to deliver

larger numbers of training sessions in situ. CBM-Ap has parallels with automating self-control, which focuses on response inhibition, as discussed below.

Implementation intentions (P1, P2, P3)

OUTLINE

This approach tries to bridge the gap between explicit Type 2 intentions and implicit Type 1 impulses. Implementation intentions are specific, concrete *if-then* plans that link particular *if* contexts (i.e. sets of cues) to a desired *then* response. They aim to automate *then* behaviour by delegating its control to the selected contextual *if* [Gollwitzer et al. 2005]. Implementation intentions are a special form of automated goals that can bridge the intention-behaviour gap [Webb and Sheeran 2006; Wood and Rünger 2016], and are argued to be a good strategy for habit formation apps [Stawarz et al. 2015].

The mechanisms through which Implementation Intentions work are increased accessibility [Webb and Sheeran 2008], so the resulting behavioural intention to perform the *then* response is highest in the Potential Response stack. Through rehearsal, sufficiently concrete and relevant Implementation Intentions become impulses, moving from Type 2 deliberative processes into Type 1 automatic processes [Einstein and McDaniel 2005].

EVIDENCE

A meta-analysis found Implementation Intentions had a medium-to-large magnitude (d = .65) on goal attainment [Gollwitzer and Sheeran 2006]. However, the meta-analysis did not consider whether the behavioural goals related to habitual behaviour or not, and other reviews note a heterogeneity in effect sizes [Hagger and Luszczynska 2014]. Prestwich et al. found some evidence that self-selected SMS reminders (*not* just-in-time reminders) can boost the effectiveness of Implementation Intentions for daily brisk walking, although the study was based on self-report [Prestwich et al. 2010].

CHALLENGES

Again, difficulties of accurately monitoring context cues and behaviour are challenges for Implementation Intention-based DBCIs. Further, evidence for habit breaking using Implementation Intentions is mixed: some research suggests they are not good at controlling strong habits [Wood and

Rünger 2016], while Sheeran et al. suggest that they have been successful with smoking interventions [Sheeran et al. 2017]. We explore technology-mediated Implementation Intentions in Chapters 5 and 7.

Provide information (P3)

OUTLINE

The provision of information is common in DBCIs [Pejovic and Musolesi 2014; Webb et al. 2010a] and behaviour change interventions in general, e.g. in healthcare [Nilsen et al. 2012]. The underlying "information gap hypothesis" [Cowan et al. 2013] implicitly assumes a rational choice model, where people alter conscious behavioural intentions (P3) to counter a given behaviour in response to information provided.

EVIDENCE

Providing information can in some circumstances change behaviour, albeit with a small impact: a meta-analysis of public information campaigns showed an average effect size of .05 [Anker et al. 2016]. Evidence is mixed for information-based DBCIs, partly because it is rarely used as a single approach. Comber & Thieme used information provision to counter habitual recycling behaviours with a just-in-time recycling-monitoring system [Comber and Thieme 2013]. They found no impact of their awareness-raising on attitudes or on behaviour over 5 weeks.

Crucially, the long-term effects of providing information on behavioural intentions are not stable. A randomised control trial with longitudinal research (12 months) showed that advising people to do more exercise is ineffective in the long term [Hillsdon et al. 2002]. The eating domain shows evidence of a persistent "mindless eating" gap of 15-20% of consumption, regardless of an individual's knowledge of nutritional information [Wansink and Chandon 2014; Bellisle et al. 2004].

CHALLENGES

Deliberative cognitive resources may not be available for Type 2 processes to attend to, analyse and deliberate the information. People also may not change their attitudes and/or behaviours in line with the information. Further, Type 1 processes may bias the information itself as an input to Type 2 processes,

e.g. framing effects, where presenting the same information in either positive or negative ways impacts differently on subsequent Type 2 judgements [Kahneman and Tversky 2000].

DBCIs often use disruption to alert Type 2 resources to process information [Verplanken and Wood 2006]. However, this is not a panacea: Combor & Thieme found that a disruptive audio signal did alert participants, but that their intervention did not provide the right information to change behaviour [Comber and Thieme 2013].

Cognitive biases in decision making also present an opportunity. Lee et al. argue that varying the way in which information is delivered, e.g. in providing the required behaviour as the default, can be successful [Lee et al. 2011]. This is a key tenet of choice architecture or 'nudge theory' [Thaler and Sunstein 2008].

Just in Time reminders (P3, F3)

OUTLINE & EVIDENCE

The strategy leverages context-aware technology to provide just-in-time reminders to behave in a particular way [Moller et al. 2017]. Reminders can support the development of habits, but can have diminishing effects [Tobias 2009]. They can also prompt reactance, where people act to restore their behavioural autonomy in response to perceived threats [Brehm 2009], particularly where users are instructed to suppress thoughts of an unwanted behaviour [Palfai et al. 1997]. As with priming, there is a risk of ironic effects [Earp et al. 2013].

Even if the 'correct' response is performed, the response may depend on the presence of the DBCI as a cue. This makes the new behaviour fragile and susceptible to disruption [Renfree et al. 2016]. Stawarz et al. found evidence in a 4-week trial that reminders increased behavioural repetition but impeded automaticity [2015]. Without automaticity, once the DBCI is removed, the behaviour is unlikely to persist.

Several researchers reduce the complexity of reminders to reduce their cognitive load. Ding et al. tried to identify low-disruption opportunistic points to deliver walking prompts using context-aware technology [Ding et al. 2016], but found embarrassment persisted at inappropriate suggestions.

CHALLENGES

Behavioural repetition in a stable context is crucial to forming automatic behaviours. Just-in-time habit-forming reminders therefore must be context-aware. However, technological issues persist in both context and behaviour detection. Few approaches to capturing behaviour also capture causal relationships between context and response [Banovic et al. 2016], limiting their ability to remind in a habit-forming way.

Training self-control (P4)

OUTLINE

Self-control is the ability to "alter [your] own behavioural patterns so as to prevent or inhibit [the] dominant response" [Muraven and Baumeister 2000]. Dual Process Theory considers self-control as a Type 2 process [Metcalfe and Mischel 1999], although it can become automated into Type 1 processes [Verbruggen and Logan 2009]. Self-control could therefore provide a mechanism for people to resist unwanted Type 1 impulses. Taylor et al. suggest that computer-based training to enhance self-control could take advantage of neuroplasticity to support treatment for drug addiction alongside pharmaceuticals [2013]. Webb, Sniehotta et al. express surprise that few interventions against addictive behaviour have used self-control strategies [Webb et al. 2010b].

EVIDENCE

De Ridder et al. found a relatively large relationship between self-control traits and habits, and suggest self-control is important in changing habitual behaviours [de Ridder et al. 2012]. Muraven argues that self-control training is generalizable: small acts of conscious behavioural inhibition improves self-control, regardless of domain or whether participants believed it would help [Muraven 2010].

Cranwell et al. found that a 3-daily, 4-week training task showed a statistically significant increase in self-control scores compared to a control group [Cranwell et al. 2014]. Research has found some impact of internet-delivered go/no-go food image tasks on weight loss [Lawrence et al. 2015; Veling et al. 2014]. Lawrence et al. trained participants to inhibit responses to unwanted foods with 4 sessions over 1 week and found a statistically significant, medium-sized drop in self-reported energy intake [Lawrence et al.

2015]. In terms of automating self-control [Fishbach and Shah 2006], Verbruggen & Logan showed that practising inhibition can automatically inhibit responses to unwanted items [Verbruggen and Logan 2009].

CHALLENGES

Effortful (Type 2) self-control is restricted by limits on deliberative cognitive resources [Baumeister 2002; Wood and Neal 2007]. When it fails, old automatic behaviours will re-emerge. The inability to introspect habits may restrict attempts to limit unwanted behaviour through self-control where people are unaware of habit cues. A strong association between affective state and self-control capacity [Economides et al. 2015; Tice et al. 2001] may also hamper behavioural persistence. Nevertheless, it is not clear precisely how the self-control mechanism works. Evidence for its efficacy is inconsistent: Miles et al. found no effects on either Type 1 or Type 2 self-control following a 6-week self-control training programme [Miles et al. 2016].

ACT: TARGET THE RESPONSE (PHASE 3)

Targeting the response aspect of the context-response link may involve the use of self-monitoring to reveal previously unknown response patterns, or operant conditioning on the response outcome (A2).

SELF-MONITORING (P5, A1)

OUTLINE & EVIDENCE

Self-monitoring involves using information from self-tracking to form alternative intentions to act [Snyder 1974]. Self-tracking, the capture and presentation of information about an individual's behaviour, can reveal information previously unknown to the user [Thaler and Sunstein 2008], such as the number of steps taken each day. The "self-monitoring and feedback" approach is highly prevalent in DBCIs [Orji et al. 2017], with domains including energy usage, water usage and activity tracking [Brynjarsdottir et al. 2012; Laschke et al. 2011; Nike+ 2013; Fitbit 2017]. Activity trackers also implement data analysis and reminder engines in addition to simple data presentation [Jawbone 2015].

A meta-analysis of 138 interventions found that self-monitoring led to small-to-medium changes in health goal attainment [Harkin et al. 2016]. Self-monitoring of weight, i.e. tracking the consequences of undesired eating behaviour, can be an effective long-term strategy in maintaining weight loss [Butryn et al. 2007; Wing et al. 2006]. Kelley et al. provide qualitative evidence that self-monitoring has a role in revealing unhealthy or unexpected behaviour [Kelley et al. 2017] and provides motivation for change.

However, self-monitoring is not a panacea for behaviour change [Epstein et al. 2016], and the evidence for technology-mediated self-tracking is not equivocal: a large-scale RCT found that using a tracking device alongside self-monitoring of diet and activity resulted in less weight loss compared to a self-monitoring group alone [Jakicic et al. 2016]. Use of activity trackers tends to tail off in the longer term: more than 50% of US tracker owners abandon their device, 1/3 abandoning it within 6 months [Ledger and McCaffrey 2014], with abandonders reporting issues with accuracy [Goodyear et al. 2017; Yang et al. 2015]. We explore this issue further in Chapter 7.

CHALLENGES

Self-monitoring and tracking is rarely implemented as a stand-alone strategy, making evaluating its efficacy difficult. Instead, it is often combined with goal setting, goal tracking and goal feedback mechanisms [Consolvo et al. 2008; Fitbit 2015]. Dual Process Theory and habit theory suggests that self-report of behaviour is unlikely to be accurate; empirical data shows substantial differences between self-report and actual sedentary behaviour [Clark et al. 2009; Colbert and Schoeller 2011].

The mechanism linking self-monitoring with behaviour change is unclear. For example, self-weighing may function as an explicit input to Type 2 processes, affecting deliberative food choices. Alternatively, self-weighing may prime Type 1 processes, triggering nonconscious restraint [Pacanowski et al. 2015; Brunner and Siegrist 2012]. The design of self-monitoring systems is important since cognitive resources to process the results of self-tracking may not always be available. This consideration has resulted in ‘glanceable’ feedback [Consolvo et al. 2008], and use of aggregated wellbeing scores [Lin et al. 2012; Meyer et al. 2014].

Revalue outcome (A2)

OUTLINE & EVIDENCE

A key strategy to revalue outcomes is providing rewards for 'correct' behaviour [Gouveia et al. 2015] or punishments for 'incorrect' behaviour [Kirman et al. 2010]. Rewards are not a necessary part of habit formation, but they may accelerate its development into automaticity. In the BAF, rewards boost the position of the matching impulse (nonconscious Type 1) or intention (conscious type 2) on the Potential Response stack. Virtual rewards are common in DBCIs [Hamari et al. 2014; Orji and Moffatt 2016], but punishment strategies are much rarer [Kirman et al. 2010]. Evidence is mixed for efficacy of virtual rewards in DBCIs, perhaps because they target Type 2 scarce resources for conscious processing of rewards. One short-term (10-day) study found no effect [Zuckerman and Gal-Oz 2014]; qualitative research both supports [Fritz et al. 2014] and does not support [Munson and Consolvo 2012] the strategy. Stawarz et al. identified a key challenge in delivering rewards to drive the generation of automatic behaviour: positive reinforcement over 4 weeks hindered automaticity, possibly due to reactance [Stawarz et al. 2015].

CHALLENGES

Accurately monitoring context and behaviour deliver rewards smoothly (so that the user assigns credit from the reward to the correct action [Maia 2009]) is not easy. The desired behaviour may be extinguished by inaccuracy: both when a given action no longer attracts the previous reward, or when a reward is received despite the appropriate action not occurring [Yin and Knowlton 2006]. It is also not clear how to apply results from psychology labs to designing rewards and reward schedules for DBCIs. Continuous or very frequent rewards can support the acquisition of new behaviours that are easily extinguished [Villamarín-Salomón and Brustoloni 2010].

Finally, punishment or removal of rewards may not alter underlying associations. Instead, people may simply learn to inhibit the unwanted behaviour in particular contexts [Bouton 2014; Redish et al. 2007], so the old unwanted behaviour may re-emerge later.

	BAF phase and target						*Challenges*				
	Filter		*Prepare*		*Action*						
Strategy	*Type 1*	*Type 2*	*Type 1*	*Type 2*	*Type 1*	*Type 2*	*Context detection*	*Mixed/ missing evidence*	*Translation to the wild*	*Cognitive limits*	*Recent implementations*
Alter context	■	■					•	•			[Kalnikaite et al. 2011; Rogers et al. 2010]
Instinctive primes	■		■				•	•			[Bateson et al. 2006; zombiesrungame 2015]
Goal priming	■	■	■	■			•	•			[Chen et al. 2014; Magaraggia et al. 2014; Loizou and Karageorghis 2015]
Alter cue salience	■		▫				•	•	•		[Enock et al. 2014; Dennis and O'Toole 2014]
Train context-response	▫		■				•	•	•		[Wittekind et al. 2015; Rabinovitz and Nagar 2015; Heitmann et al. 2017]
Implementation intentions	■	■	■	■			•				[Veling et al. 2014; Brevers et al. 2017; Thompson et al. 2012]
Provide information				■				•		•	[Comber and Thieme 2013]
JIT reminders				■			•	•		•	[Klasnja et al. 2015; Ding et al. 2016]
Self-control			▫	■		■	•	•	•	•[4]	[Lawrence et al. 2015; Miles et al. 2016; Blackburne et al. 2016]
Self-monitoring				▫		■	•	•		•	[Kelley et al. 2017; Hollis et al. 2015]
Revalue outcome			▫	▫	■	■	•	•	•		[Adams et al. 2017; Fitbit 2015]

■ *Direct target* ▫ *Indirect target*

Table 3:2 Strategies, BAF phase and Type 1/Type 2 targets

[4] Note that self-control also has a Type 1 component that is less affected by cognitive limits than its Type 2 counterpart

Summary

Which strategies hold most promise as approaches for further research? Table 3:2 shows an overview of the identified strategies, together with the processes they target, which component of habits they relate to (illustrated with reference to the BAF Figure 3.1), a summary of the challenges and recent implementations.

The main challenges are: correct context detection; mixed or missing evidence for a strategy's efficacy in relation to behaviour changes; difficulties in ecological validity, i.e. in translating strategies from psychology labs to in-the-wild DBCIs; and interventions that rely on limited deliberative cognitive resources. Context detection issues affect most strategies. This may explain why information-providing DBCIs are common, while few DBCIs use context analysis [Stawarz et al. 2015; Honka et al. 2011]. The empirical gaps indicate opportunities for research.

The techniques we selected for further investigation were those that target Type 1 processes, have shown promise in psychology labs, are transferable to digital interventions, but have yet to be explored in-depth in DBCIs: Implementation Intentions, cognitive bias modification (both Attention and Approach varieties) and subliminal priming. We outline our reasons below.

Implementation intentions (Chapter 4)

Implementation intentions are a good candidate strategy because they effectively model habitual behaviours and are predicated on stable environments. They focus on shifting conscious Type 2 goals into automatic Type 1 processes (moving from P3 to P1 in Figure 3.1). There is also good evidence of a moderate-to-large impact of the strategy on behaviour from a meta review [Gollwitzer and Sheeran 2006]. Although some studies have ported the strategy out of psychology labs onto SMS-based systems, e.g. Pirolli et al. [2017], there is still a research opportunity in exploring how it might be enhanced by using more pervasive context-aware technology. Stawarz et al. argue that Implementation Intentions should be used to help support habit formation in apps, and suggest further research is required into its use on mobile technologies [2015].

A caveat to employing Implementation Intentions is the ongoing challenge in solving problems of accurate behaviour and context-detection [Bettini et al. 2010; Rogers 2006]. However, Tobias argues that in-situ reminders can support the accessibility of Implementation Intentions [Tobias 2009], while evidence shows that even inexperienced users can quickly learn if-then plans with multiple triggers or actions [Ur et al. 2014]. Therefore, we identified an opportunity to explore the use of

context-aware technology triggers to support Implementation Intentions. Exploring Implementation Intentions with context-aware technology was therefore our starting point in exploring NDBCIs, and is the focus of the next chapter.

Cognitive Bias Modification (Alter cue salience, Train context-response; Chapter 5)

CBM techniques to alter cue salience and train context-response actions (CBM-Attention and CBM-Approach respectively) are good candidate strategies because they have shown promise in psychology labs, but have been little-used in DBCIs. Further research is therefore warranted to establish how the techniques might translate to DBCIs. To avoid context-detection issues, we selected two domains where the unwanted cues are relatively easy to identify (healthy eating domain – unhealthy food cues; smartphone problematic use domain – smartphone cue). The use of the technique may also confer particular advantages in the healthy eating domain compared to a self-tracking approach since people have a generally poor ability to monitor their food consumption [Wansink and Chandon 2014]. CBM tends to use rehearsal or training of the desired different attention or approach actions, rather than using explicit behavioural directions. They are therefore less likely to provoke user irritation and reactance than disruptive just-in-time behavioural prompts.

Subliminal priming (Chapter 6)

Subliminal priming is a good candidate strategy because as noted above, using priming may result in increasing the value of related impulses on the Potential Response Stack (P6). As with CBM, subliminal priming techniques do not tax deliberative cognitive resources, and are therefore less likely to trigger reactance. They can also support habit formation where the automated behaviour occurs in a stable context. We propose examining the use of subliminal goal priming to increase the accessibility of related behaviour, and thus increase the likelihood of the goal-related behaviour being enacted (see Chapter 6 and [Custers and Aarts 2007]). This avoids the context-detection issues since the priming can occur regardless of context; since it is delivered below the threshold of conscious awareness, it gives us an opportunity to avoid possible reactance and user irritation by getting the time-of-delivery wrong. Further, there is a research gap in determining the most effective method of subliminal priming, since there are a wide range of priming design choices including design of the prompt, duration, repetitions required and delivery mechanism.

The next chapter outlines our research into the use of context-aware technology to support Implementation Intentions.

4. EXPLORING CONTEXT-AWARE IMPLEMENTATION INTENTIONS ON SMARTPHONES

This chapter:

- presents the results of a smartphone-based context-aware Implementation Intentions pilot carried out in-the-wild over one week (4.1);
- analyses responses to a qualitative survey to identify good candidate locations for behaviour change proximity triggers in the workplace and at home (4.2); and
- derives a set of key design recommendations and pointers for future research.

The pilot study 4.1 was built and tested as part of a student project I supervised by Adhi Wicaksono. The related work, data analysis, discussion and rest of the chapter was solely my own work.

MOTIVATION

Implementation Intentions are special *if-then* plans where *if*s are contextual cues and *then*s are specific goal-related behaviours. We outlined in Chapter 3 why they hold promise as an effective strategy to support the formation of automatic behaviours: their evidence base from psychology is good, and they model habitual behaviours. Yet they still face the problem of accurate context-detection. Therefore, to investigate RQ2, "how can technology best exploit nonconscious opportunities to intervene in a user-friendly way", given that context-aware technology might help us to overcome context-detection problems in NDBCIs, we undertook both pilot 4.1 to explore how people might use context-aware support on smartphones in Implementation Intentions, and a survey 4.2 to better understand the potential role of context triggers in this sort of NDBCI.

INTRODUCTION

Implementation Intentions are specialised goal intentions that explicitly set up contextual cues as triggers (e.g. time of day or a particular location) for a desired goal-related behaviour (e.g. to take the stairs) [Gollwitzer 1999].

Implementation Intentions aim to automate behaviour, i.e. to convert intentional behaviour into a nonconscious habit, by rehearsing cue-behaviour associations in memory such that the link achieves a "heightened accessibility" and becomes a candidate for automatic activation [Gollwitzer 1993]. Sheeran et al. suggest Implementation Intentions may also protect people against adverse goal primes in the environment (e.g. advertising) [2005a]. Gollwitzer & Sheeran's meta-analysis found

Implementation Intentions had a medium-to-large effect on goal achievement, with evidence that Implementation Intentions increased accessibility of goal plans and goal automation [2006].

Design issues

Implementation Intentions require the identification of appropriate contextual triggers and the ability to combine these *if*s into *if-then* plans [Verhoeven et al. 2014]. *Appropriate* triggers are those that are "sufficiently salient in daily life … encountered and detected frequently and consistently" [Gardner et al. 2012b]. Ur et al. demonstrated that novice users can learn to generate plans with multiple *if*s and *then*s [Ur et al. 2014]. *If-then* "recipes" have been implemented in the web & app service If This Then That (IFTTT) [2015] and in other smartphone-automation apps e.g. [Tasker 2016]. IFTTT allows users to link devices and social media services to automate tasks, with more than one million *if-thens* created [If This Then That 2012] and 100,000 users [Ur et al. 2016]. Although these services do not focus on behaviour change, they indicate that if-then programming may be easily grasped.

Study 4.1 Implementation Intention Pilot

This study was carried out as part of a student project by Adhi Wicaksono.

Motivation

Therefore, we wished to explore how context-aware smartphones might convey some advantages to support the *if* (i.e. context trigger) component in Implementation Intention if-then plans. Implementation Intention studies on smartphones e.g. [Prestwich et al. 2010] tend to use SMS text messages to support interventions, and do not use smartphone context detection as a possible trigger. DBCIs using Implementation Intentions are starting to emerge, e.g. [Thompson et al. 2012] who focused on using video games as a delivery vehicle, but to our knowledge this was the first research into Implementation Intentions using the context-aware capabilities of smartphones.

Method

We built a pilot on Android smartphones to explore how users interact with a context-aware Implementation Intentions app. The app enabled users to combine *if* context triggers with *then* goal-related behaviours to generate Implementation Intentions. When the relevant *if*s were detected for each II, the app notified users with an alert and text to remind them of their related *then* goal-related behaviour.

Design

The pilot used a simple pre-test/post-test single group quasi-experimental design as a design probe to gain more insights into how people might use their context-aware smartphones to support Implementation Intentions.

Hypotheses

Our hypothesis was that there would be a statistically significant effect of session on goal automaticity scores. We predict that the score would increase between pre- and post-tests.

Participants

10 Android users were recruited from the student population of the University of Birmingham. We did not record additional demographics information.

Materials

Participants used their own Android smartphones to install our experiment app and specify Implementation Intentions. *If* context triggers available in the app were: location, movement, time, calendar, device battery and orientation.

Figure 4.1 shows an example Implementation Intention with two combined cues, while Figure 4.2 shows an example list of goal-related behaviours that have been added to cues to generate Implementation Intentions.

Figure 4.1 Example Implementation Intentions showing goal and related trigger cues

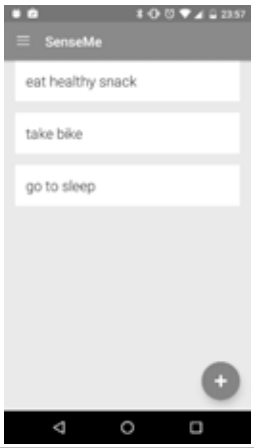


Figure 4.2 Example Implementation Intentions list

Measures

Our dependent variable, goal automaticity, was a sub-scale of the Self-Report Habit Index (SRHI,[Verplanken and Orbell 2003]) to measure the automaticity of their selected goal-related behaviours (Table 4:1), with a 7-point Likert scale. We omitted self-identity items since it has been found to not measure habit [Gardner et al. 2012a] and longevity of behaviour due to our short intervention. Our independent variable was session, pre- and post-intervention (within-subjects). At post-intervention, participants also completed a System Usability Scale (SUS, [Bangor et al. 2008]) questionnaire as a quick, high-level subjective participant view of system usability.

I do that behaviour automatically
That behaviour makes me feel weird if I do not do it
That behaviour would require effort not to do it
I would find hard not to do that behaviour
I do that behaviour without having to consciously remember
I do that behaviour without thinking
I start doing that behaviour before I realise I am doing it
I have no need to think about doing that behaviour

Table 4:1 SRHI subscale items

Procedure

Participants first completed the SRHI sub-scale. Participants then installed the app and received instructions in person on generating Implementation Intentions from *if* context triggers and *then* goal-related behaviours. After one week, participants filled in a post-test SRHI and the SUS.

RESULTS

SRHI

We examined SRHI values to test our hypothesis that the scores would be higher at post-intervention compared to pre-intervention. Descriptive statistics are shown in Table 4:2, and Figure 4.3 shows a barplot with one-standard-error error bars.

The differences were tested for normality (Shapiro-Wilk W=0.88, p=.12). A paired t-test showed no evidence of a statistically significant difference between the means $t(9) = 1.21$, $p = .26$), with a mean difference of 0.63, 95%CI[-1.80, 0.55], Cohen's d=0.38.

Session	*SRHI Mean*	*95%CI*	*SRHI SD*
Pre	4.58	[3.30, 5.85]	1.78
Post	5.20	[4.41, 5.99]	1.10

Table 4:2 SRHI descriptive statistics by Session

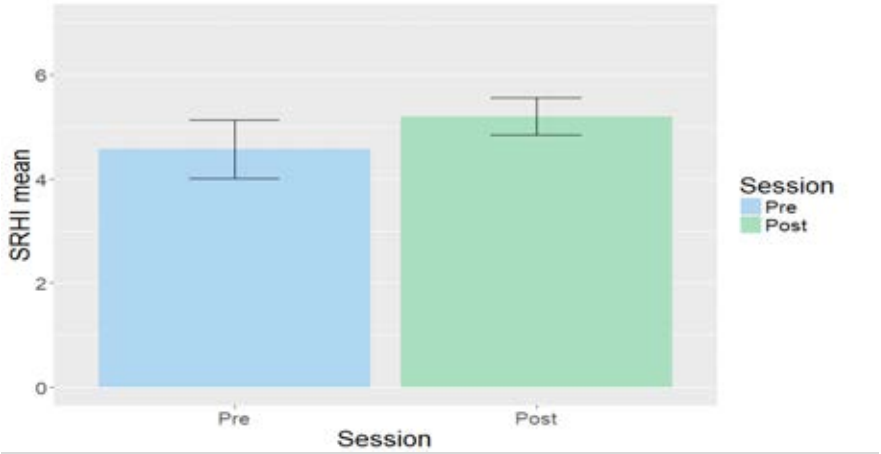


Figure 4.3 Barplot of SRHI means with 1SE bars

SUS

The mean SUS score was 71.75, indicating that from a subjective participant viewpoint there was no self-reported evidence of major usability problems [Bangor et al. 2008; Brooke 2013].

QUALITATIVE RESULTS

Table 4:3 shows the Implementation Intentions created by participants. All participants only created one II, and the context cues used were broadly similar.

If …	*Then …*
Movement	Walking 30 minutes a day
Movement	Thin
Location	Sleep tight
Time	Jogging after dinner
Time	Exercise for 10 minutes
Movement	Walking
Time	Drink water
Time	Jogging
Location, Time	Having a dinner

Table 4:3 1 Implementation Intentions created

No participants used the calendar, device battery or orientation cues as Implementation Intention cues. Then goal-related behaviours all focused on health, with 7/10 related to exercise and movement, 2/10 relating to food and water intake and the remaining goal going to sleep. If context triggers included movement (4 Implementation Intentions), time (4 Implementation Intentions), location (1 II) and location + time (1 II). Most of the goals (e.g. "Thin" and "Walking") were somewhat abstract; only two are more specific – "exercise for 10 minutes" and "jogging after dinner" - and these still could do with more detail (e.g. what type of exercise?; how long to jog for and where to?) in order that they are salient to participants.

Discussion

There was no evidence for our hypothesis that the intervention would result in a statistically significant increase in our measure of goal activation (SRHI). Given that 95%CIs for normal data are approximately 2 standard errors from the mean[5], we can see from figure 4.3 that this experiment would only be able to detect differences of approximately 2 units on the SRHI scale (0-7). The experiment is therefore underpowered, so there is a risk that our non-statistically-significant result may be a false negative. The experiment also has a small-to-medium effect size of 0.38, so the difference is non-trivial, albeit not statistically significant.

One method to reduce standard error is to increase n. To halve the standard error, the sample size must quadruple since the standard error is equal to the sample standard deviation over the square root of the sample size. Therefore, to achieve confidence intervals approximately the same as the standard errors shown in figure 4.2, to detect changes of around one unit on the SRHI, we could

[5] the critical t value for d.f. = 9 at 95% confidence is 2.26, so 95%CIs are mean +- 2.26 * standard error.

repeat the experiment with an n of 40. Alternatively, or in addition to increasing sample size, we could take other measures to gain power [Dix 2017], for example to run a more controlled experiment.

Given the positive results from meta reviews of Implementation Intentions, we still consider this a NBCI with potential. We use possible reasons for goal failures from this experiment to feed into a Goal Failure Framework in Chapter 7. That chapter reconsiders adopting Implementation Intentions by proposing a more structured intervention with more support for forming, rehearsing and chaining Implementation Intentions that has the potential to have a greater impact with lower variability.

In terms of RQ2, "how can technology best exploit nonconscious opportunities to intervene in a user-friendly way", we found little evidence to suggest that context-aware smartphones can overcome context-detection problems. Indeed, this study indicated that users require additional support during the Implementation Intention creation phase: the goals created were somewhat abstract and the salience of the selected cues may not be strong, given that most participants only used one cue e.g. time.

Although the SUS score indicated no self-reported usability issues, most users (9/10) only specified one goal using one cue, and their *then* plans were not all concrete activities. This indicates possible intelligibility issues in forming context-aware Implementation Intentions. Future research is needed to clarify whether users prefer to only set single *if-then* plans, and what the upper limit is for multiple plans.

Limitations

This quick-and-dirty pilot was limited by a small number of participants and no control group, therefore the power was low and it is difficult to draw conclusions about a lack of evidence for changes in SRHI. Our focus was in exploring what Implementation Intentions participants form using a context-aware system. We did not measure how often the if-then plans were triggered which would have provided further information on their suitability, and may also have altered our measure of goal automaticity. The intervention was short; only running over one week, which is unlikely to be sufficient time for automatic behaviour to emerge given evidence that they can take 18-254 days to form [Lally et al. 2010]. We enabled smartphone-specific context cues such as device orientation and battery level which may not fit the criteria for trigger cues to be salient and detected [Gardner et al. 2012b]; we found no evidence that participants found these cues helpful since none used them. We did not record or score any of the interactions with participants during the setup phase, which may

also reveal other intelligibility issues. The participant information material may have primed them to set only one II.

Therefore it is not clear how good people are at identifying appropriate cues and/or if the tech-supported cues were suitable to form Implementation Intention anchors. It is perhaps not surprising that our participants did not base their intentions on non-obvious technology context options such as device battery or orientation, and the intervention may have had too short a life to make the calendar a useful cue option. To disambiguate this issue, we ran a qualitative survey as outlined in the next section.

Study 4.2: Elicitation survey

Motivation

We wished to broaden our understanding of how context-aware technology can best support Implementation Intentions beyond smartphones. We therefore used a survey to ask potential users about potential application domains. We also explained the concept of proximity triggers, without mentioning a specific technology, and then gathered information about specific locations that potential users would wish to place such triggers in, based on locations at work and in the home whether they perform unwanted habitual behaviours.

Method

Participants

137 people (mean age 30.7 years, SD 11.97, 100 female) took part. The majority (56%) were students.

Procedure

Participants were recruited via social media and completed the survey online. They gave informed consent, provided demographics information and could optionally enter a prize draw on survey completion. We asked them to report any repetitive behaviours they wanted to change (creating new habits or breaking old ones) and where they performed them (at home and at work). Then we asked where they would place technology to detect when they were close to a particular place or object to support them to change their behaviour (proximity triggers), and why. We gave examples of a trigger on a water cooler to remind them to drink more water, and one by the lift to remind

them to take the stairs. We asked how triggers should alert people, and what they should say to persuade them to comply. Full questions are given in the Appendix.

RESULTS

DATA ANALYSIS

Responses were analysed using content and thematic analysis [Braun and Clarke 2006]. They were iteratively coded, and grouped into object categories or behaviour themes. Following Kennedy et al. [2013], each response could contribute a maximum score of 1 to any particular category, and any response could contribute to multiple categories. We discuss the categories below.

LOCATION AND OBJECT CUES

For both home and work, responses were of two types: specific locations and particular objects in those locations. Table 4:4 shows categorised mentions for home-specific locations and objects; Table 4:5 shows the same for workplaces. Food issues feature strongly in both: the kitchen is the top home location, and food outlets topped the work location list. Top objects at home are fridge and food storage (e.g. biscuit tin), while food storage, vending machines and workplace fridges all feature in work objects.

Home location	*Mentions*	*%*	*Object*	*Mentions*	*%*
kitchen	38	28	fridge	30	22
entrance/exit	12	9	food storage	23	17
lounge	12	9	TV	21	15
bedroom	9	7	desk	10	7
bathroom	5	4	sofa	9	7
study	3	2	bed	9	7
stairs	2	1	computer	8	6
lift	1	1	phone	7	5
drive	1	1	car	5	4
			exercise equipment	4	3
			freezer	4	3
			kettle	4	3

Table 4:4 Top 10 home locations/objects mentioned

Office location	*Mentions*	*%*	*Object*	*Mentions*	*%*
food outlet	19	14	water cooler	20	15
lift	13	9	computer	15	11
kitchen	11	8	desk	14	10
entrance/exit	7	5	fridge	11	8
office	4	3	food storage	8	6
bathroom	3	2	vending	5	4
bus stop	3	2	phone	5	4
stairs	2	1	mirror	2	1
car park	2	1	light switches	2	1
pub/bar	2	1	chair	2	1

Table 4:5 Top 10 themed office locations/objects mentioned

TARGET BEHAVIOURS

Target behaviours were categorised as *positive* where the goal was to perform the behaviour; and *negative* where the goal was to stop performing it. Target behaviours for home and work are shown in Table 4:6 and Table 4:7 respectively.

Positive behaviour	*Mentions*	*%*	*Negative behaviour*	*Mentions*	*%*
exercise/ breaks	21	15	stop snacks	18	13
eat healthily	15	11	procrastination/ distraction	7	5
drink water	10	7	stop being sedentary	3	2
floss / clean teeth	3	2	Stop smoking	1	1
read more	3	2			
tidy/wash up	3	2			
lock up / remember keys	3	2			

Table 4:6 Home target behaviour theme mentions

The top four positive home behaviours, 3 of the 4 negative home behaviours, the top 4 positive workplace behaviours and half of the four negative workplace behaviours are all related to health.

Positive behaviour	*Mentions*	*%*	*Negative behaviour*	*Mentions*	*%*
exercise/ breaks	17	12	procrastination/ distraction	6	4
eat healthily	17	12	stop snacks	3	2
drink water	17	12	drink less coffee	2	1
take stairs	5	4	don't smoke	1	1
energy saving	3	2	drink too much	1	1
			spend too much	1	1

Table 4:7 Workplace target behaviour theme mentions

Notifications: when and how

There was a wide variety of suggested modes of interruption, from specifically unobtrusive vibration ("vibrate to be discreet", "silent vibrate") to deliberately annoying ("In the most annoying way possible so that it can't be ignored"), via loud noises and alarms. One user suggested a solution: "*You should be able to choose the alert sound or vibrate that suits you. The alert should self-destruct if not responded to within a particular time frame*".

Notification content

Results are shown in Table 4:8, with simple goal reminders only a minority of suggestions (40%). They suggest users prize configurability, both in notification *mode* (vibration, noise, lights etc.) and *content*. The results also indicate users expect context-aware apps to be able to predict behaviour. Several people specifically requested *negative* reminders, e.g. "*near coffee shops, to not go in*" (P23), "*stop me from looking a[t] my phone*" (P40).

Type	*%*	*Examples*
simple goal reminder	40%	
outcomes reminder	13%	"show me an image of rotten teeth"
context-aware reminder	9%	"linked to the pedometer"
generic reminder	9%	"stop!", "think"
tailored reminder	9%	users can "set [their] own phrases"
sound or vibration only	8%	

Table 4:8 Reminder type themes mentioned by % of users

Issues with JIT interruptions

Table 4:9 summarises reported issues.

Issue	*Mentions*	*%*
Annoying alerts	16	12
Reactance	16	12
Ignore alerts	10	7
Context-aware issues	10	7
Longer term failure	6	4
Miss alerts	5	4
Cognitive load	1	1

Table 4:9 Reasons for failure

Although we implied reminders would always appear in the presence of a given trigger, 6 participants (4%) suggested such reminders might lose impact in the longer term, e.g. "*I tend to start ignoring them after a bit*" (P131). 10 participants (7%) identified the importance of reminding in the right context. If cues appear at the wrong time, and the required behaviour is not enacted, over time people may form an automatic response to ignore the cue: "*if you have something reminding you at set times of day then you'll just get used to it*" (P4). Participant P41 asked for an "*alert [only] when it is appropriate*", wanting the app to be aware of their other activities and/or calendar. Reactance was identified as a potential issue by 16 participants (12%) if the app is triggered at an inconvenient time: "*If I got too many notifications when I'm not able to go through with the task I'd probably get a bit annoyed and turn them off entirely or delete the app*" (P44), "*if it isn't 'smart' it could become frustrating and may make you turn the app off*" (P5). 16 participants (12%) speculated that context-aware alerts would be annoying, while 10 participants (7%) suggested that they might ignore predictable reminders.

Finally, this approach would not appeal to everyone: 11 people (8%) rejected the idea of proximity triggers at work, one because they are retired, while 10% (14%) rejected the idea of proximity triggers in the home. One person commented, "*I would HATE this and avoid these places*" (P36).

Discussion

In terms of RQ2, we have established some evidence of what sorts of intervention would be valued. Health-related behaviours dominate user concerns both at home and at work: the top 3 positive behaviours in both locations are exercise, eating healthily and drinking water. Other overlaps include requirements to guard against procrastination and distraction.

We also found evidence of a wide variety of suggested notification modes alongside evidence of issues with Just-in-Time interventions including irritation and possible reactance. Therefore, highly tailorable interventions are likely to be the least disruptive; we revisit this point in Chapters 7 and 8.

Limitations

Note that our survey questions included examples of watercooler/drink more, and lift/take stairs interventions. Their popularity should be validated by a study that does not cue these examples. Our study analysis was limited by the content and thematic analysis only being undertaken by one researcher.

Summary

Overall, we found qualitative evidence that some users dislike just-in-time interventions as currently implemented, with annoyance, reactance and ignoring as key reasons for disliking them. There is a clear requirement for more training at formation of Implementation Intentions than we applied in our pilot: we found many examples of negative behaviours, which risk ironic effects in Implementation Intentions [Adriaanse et al. 2011]. We therefore re-visit the training option, alongside other possible avenues for further research with Implementation Intention NDBCIs to enhance their efficacy, in Chapter 7, where we examine how such interventions can address potential sources of goal failure.

The research in this chapter provides insights into the augmentation of Implementation Intentions using context-aware smartphones, as part of addressing RQ2, "how can technology best exploit nonconscious opportunities to intervene in a user-friendly way".

To provide a user-centred design, future Implementation Intention apps should:

1. Support strong configurability for 'if' proximity triggers to include room-level locations and specific objects (4.2);
2. Guide users during the Implementation Intentions formation phase to avoid negative behaviours and form goals with appropriate specificity (4.1, 4.2);
3. Support user tailoring for notification timings, mode and content, integrating with user calendars where possible, since our survey 4.2 showed support for configurable notifications;
4. Manage context-aware expectations (4.2);
5. Expect some users to be resistant to the app, and test for reactance (4.2).

The use of Implementation Intentions remains a good candidate strategy for NDBCIs because of the strength of evidence for their efficacy in metareviews, and the way they effectively model habitual behaviours. Our survey 4.2 also showed user interest in the approach. Although our study 4.1 found no evidence of efficacy, we note that it was underpowered. We therefore return to considering how they may be incorporated into NDBCIs further in Chapters 7 and 8.

We also identified several potential limitations of the specific just-in-time context-aware interruption approach that we took. Our survey 4.2 showed issues of reactance and annoyance with the sort of interruptions we used in our pilot. Reminding users of *then* goals in the presence of *ifs* also risks user distrust if the app cannot reliably detect whether the user has just performed, or is anyway about to perform, the required behaviour. Yet even if this context- and behaviour-detection problem were solved, reliable 'correct' reminders might also be habitually ignored by users.

In Chapter 7 we consider how Implementation Intention NDBCIs may address several potential sources of goal failure through defensive design, using strategies of rehearsal, chaining and warning of possible conflicts between triggers and cues. Chapter 8 outlines other future research questions for the technique.

In the shorter term, we shifted research focus to explore an alternative, less disruptive strategy: cognitive bias modification. This emerged as another candidate strategy from the BAF in Chapter 3. This is the subject of the next chapter. The approach moves down the cognitive load continuum to a more lightweight interaction less likely to induce reactance because it does not involve direct behavioural commands. It also avoids the requirement of just-in-time context detection by focusing on a time-shifted training element for the required behaviour ahead of behavioural enactment time.

5. COGNITIVE BIAS MODIFICATION

This chapter discusses two experiments and a qualitative survey exploring the use of cognitive bias modification (CBM) as a nonconscious intervention strategy. It covers:

- Experiment 5.1, in the healthy eating domain, using an elicitation study and a pilot longitudinal intervention to explore opportunistic incidental CBM on smartphones to retrain attitudes to healthy and unhealthy foods.
- A follow-up qualitative survey, study 5.2, exploring how users might like to use CBM training, and their domains of concern.
- Experiment 5.3, which builds on reported user concerns about problematic smartphone usage, uses a single-session intervention to explore the use of a Tabletop to retrain approach and avoid biases towards smartphones.

Experiments 5.1 and 5.3 were carried out as part of student projects I supervised, by Rosa Lilia Segundo Díaz, and Jose Ignacio Rocca respectively. Related work, data analysis, discussion and survey 5.2 were all my own work.

MOTIVATION

Chapter 3 identified a research gap in exploring how DBCIs can use CBM outside psychology labs, and Chapter 4 indicated user issues in intelligibility and with just-in-time behavioural prompts. This chapter explores an alternative in using simple training strategies to alter nonconscious processes. Our motivation was to explore the application of CBM-Attention (CBM-A) and CBM-Approach (CBM-Ap) in-the-wild and in semi-controlled conditions to assess their suitability for further research.

INTRODUCTION

Chapter 3 outlined how CBM-A and CBM-Ap techniques can target the nonconscious Filter and Prepare BAF stages. CBM-A aims to alter an attention bias (a Type 1 attention process) towards a particular cue and/or away from a particular cue e.g. [Dandeneau et al. 2007; Kakoschke et al. 2014].

CBM-Ap targets automatic approach/avoid cue-triggered behavioural impulses within Type 1 memory processes, e.g. [Scott-Brown et al. 2012; Wiers et al. 2011; Wittekind et al. 2015]. Chapter 3 noted a key piece of CBM-Ap research was Wiers et al.'s approach-avoid task (AAT). Just four sessions of a CBM-Ap AAT training using a joystick (push away images of alcoholic drinks, pull

towards you images of soft drinks) had short-term effects on Implicit Association Test scores and a marginally statistically significant impact on relapse rates after 1 year [2011].

Few CBM interventions have targeted smartphones or tablets to deliver training. A pilot healthy-eating CBM-Ap tablet game replicated the push/pull paradigm with swipe up/down touchscreen gestures but is yet to show results [Scott-Brown et al. 2012]. Enock et al. found mixed statistically significant effects for a social anxiety CBM-Ap app, but concluded smartphones are a viable tool to deliver reaction-time based assessments [2014]. Several commercial CBM apps claim to help with social anxiety, problematic eating and smoking [Bias Modification Therapy 2015; Mental Mint 2015a; Mental Mint 2015b], but evidence for their efficacy is unclear.

Experiment 5.1: "Accept the banana"

This study was carried out as part of a student project by Rosa Lilia Segundo Díaz.

Motivation

We wished to explore the application of CBM techniques to smartphones in the healthy eating domain. We selected the healthy eating domain because of evidence from our surveys that people are interested in using technology in this domain, and evidence it is a pressing problem: some OECD countries may have 2/3 of their population obese by 2020 [Sassi 2010]. Kakoschke et al. found that CBM can impact eating behaviour, with a single-session of CBM-A training increasing both attentional bias for and consumption of healthy foods [2014].

Our approach differs from existing CBM research in several ways. Firstly, rather than assuming that push/pull map to reject/accept gestures [Scott-Brown et al. 2012], we used an elicitation study to determine how users accept/reject items on smartphones. Secondly, CBM training was incorporated as part of an opportunistic incidental interaction [Dix 2002; Ding et al. 2016], piggy-backing existing smartphone actions (unlock activity) rather than as a standalone. To our knowledge, this is the first intervention to apply CBM in an incidental way on smartphones. Finally, the intervention prioritised showing healthy foods over unhealthy foods at a ratio of 9:1 to counter possible ironic effects where unhealthy food images cue users to eat those foods [Earp et al. 2013; Adriaanse et al. 2011], and to increase liking via the mere exposure effect [Zajonc 1968a]. Our approach therefore combines CBM-A and CBM-Ap since participants were shown more healthy than unhealthy foods.

Measuring eating behaviour is difficult, even with self-report. Instead we used specific and general food attitudes as a proximal outcome [Klasnja et al. 2011]. Our research question was whether this blend of CBM-A and CBM-Ap would change both specific and general participant attitudes towards healthy foods and their ratings of them.

We first established which gestures people tend to use for 'accept' and 'reject' on smartphones via an elicitation study. We applied the resulting gestures in an opportunistic intervention within a smartphone unlock screen, and ran a pilot pre-post-control group study in-the-wild to explore its impact on specific and general attitudes to healthy and unhealthy foods.

Elicitation study

This study was run to determine which gestures participants use to indicate 'accept' and 'reject'.

Method

Participants

9 masters students were recruited from the University (3 women, 6 men; 8 right-handed; no age data gathered). All participants owned a smartphone (6 Android users; 3 Apple users).

Procedure

Participants completed a consent form. They 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 (red and green). They were instructed to perform any gesture to reject or accept the shapes, three gestures for each shape. After three gestures were recorded, the image changed to the next one. Full instructions are given in the Appendix.

Results & discussion

Figure 5.1 and Figure 5.2 show aggregated results from the Accept and Reject conditions respectively.

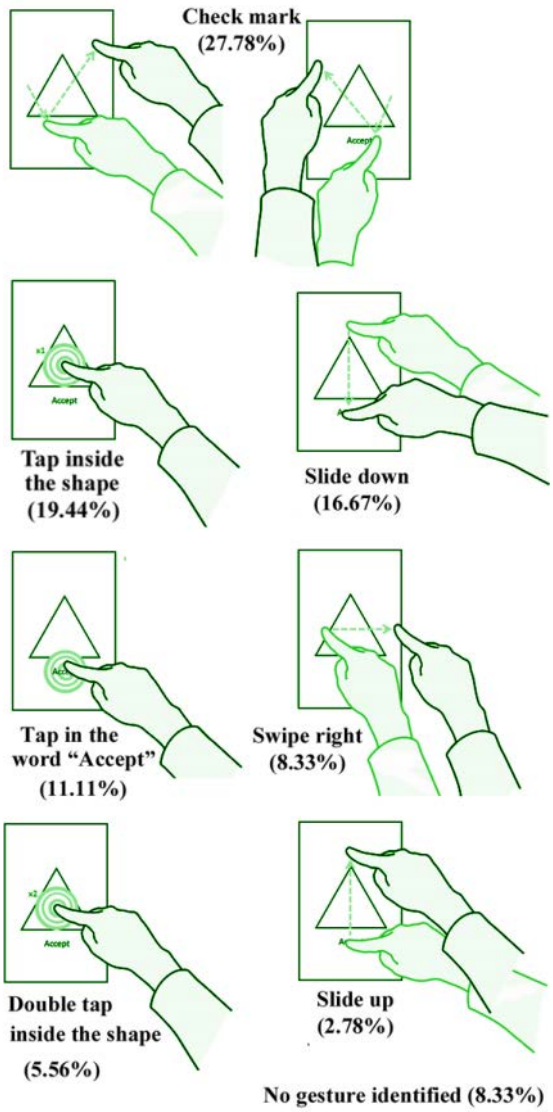


Figure 5.1 "Accept" gestures

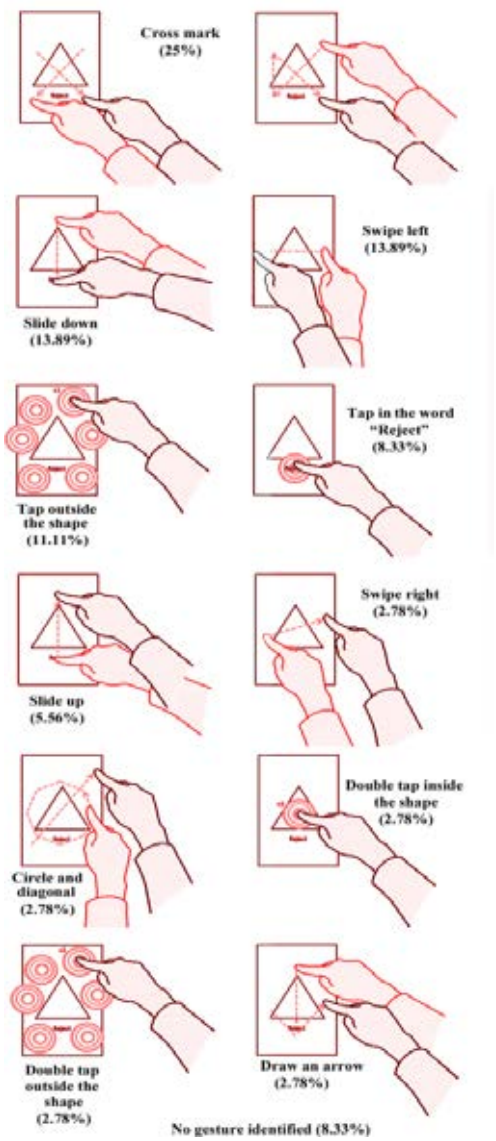


Figure 5.2 "Reject" gestures

We disregarded double tap gestures due to possible priming effects because this gesture was used to start the experiment. The results show no clear overall agreement on accept or reject gestures. Both "slide up" and "slide down" – the most directly mapped gesture from the CBM-Ap push-pull paradigm – appear on both lists, making these gestures unsuitable. The top gestures in each condition, tick mark and cross mark, formed a logical pair, so these were selected for the pilot app.

Pilot intervention

We applied the findings from the elicitation study to an app to deliver opportunistic incidental CBM-Ap and CBM-A training at smartphone unlock time.

METHOD

DESIGN

The pilot used a pre-test/post-test control group design. Our independent variables were intervention group (control and intervention, between-subjects) and session (pre and post, within-subjects). There were two sets of dependent variables: specific and general measures of food attitudes.

HYPOTHESES

We hypothesised that there would be a statistically significant interaction between intervention group and session. We predicted that, when compared to the control group, participants in the intervention group would show increased positive attitudes towards healthy foods and decreased positive attitudes towards unhealthy foods at post-test compared to pre-test measures.

PARTICIPANTS

22 participants (who had not participated in the elicitation study) were recruited from the University and the researchers' social networks (age: mean=29.1 years, *SD*=9.7 years; 10 women). 12 were Android users who were assigned to the intervention group, the other 10 participants acted as the control.

APPARATUS

Intervention participants installed an app on their own Android smartphones that on unlock showed an image of either a healthy or unhealthy food as a full-screen overlay. A stylised version of the intervention is shown in Figure 5.3. To unlock their phone, participants had to perform a tick (check) gesture to accept healthy items, or a cross gesture to reject unhealthy items. If the participant performed the wrong, or an unknown gesture, 3 times, the phone was unlocked and a reminder message was shown to indicate the correct expected gesture. This overlay appeared in addition to any other unlock screen because of security concerns.

The prime picture shown on the overlay was randomly selected from a group of 10 healthy food images and 10 unhealthy food images in a ratio of 9:1.

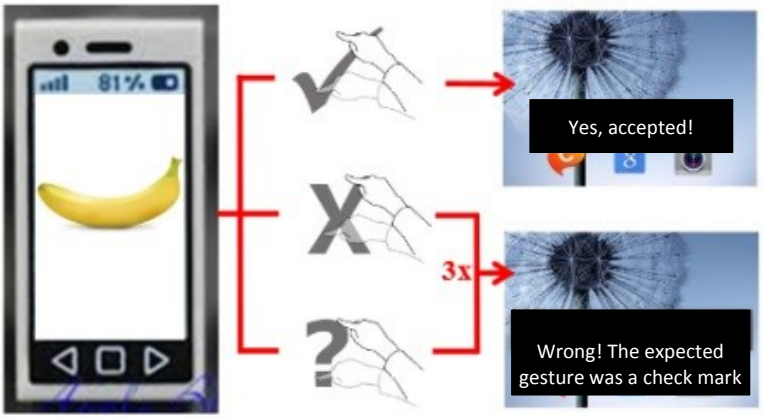


Figure 5.3 Healthy food unlock procedure

MEASURES

Our dependent variables were in two categories: specific measures of the items used in the experiment (healthy and unhealthy food images) and general measures of attitudes to healthy and unhealthy foods in general.

SPECIFIC MEASURES

There is some debate over the appropriateness of implicit measures such as the emotional Stroop test for eating-related studies [Phaf and Kan 2007]. Instead, we chose a lightweight measure of specific food liking by using a pleasantness rating on a 7-point scale from “extremely unpleasant” to “extremely pleasant” for the experiment set of (a) healthy (HFIR) and (b) unhealthy (UHFIR) food images.

GENERAL MEASURES

We used four general measures of food and food-related attitudes. These included two Health and Taste Attitude Scale (HTAS) [Roininen et al. 1999] subscales, (a) General Health Interest (GHI) items, and (b) Taste items. The scales have been validated in multiple experiments across countries [Roininen et al. 2001]. Full HTAS components are given in the Appendix. The third and fourth general measures were 7-point Likert attitude ratings using 6 semantic differentials [Osgood 1952] as shown in Figure 5.4 , one for “healthy food” (HFA) and one for “unhealthy food” (UHFA), as a relatively lightweight measure of affect. Semantic differentials are a common technique to measure users’ perception and evaluation of concepts and objects [Hassenzahl et al. 2001]. They are used in HCI broadly to measure affect e.g. [Creed et al. 2015] and have been used in previous food interventions [Pettigrew et al. 2015].

Semantic differentials for healthy and unhealthy food
Important | Unimportant
Harmful | Beneficial*
Healthy | Unhealthy
Enjoyable | Unenjoyable
Pleasurable | Unpleasurable
Satisfying | Unsatisfying
**reverse scored*

Figure 5.4 Semantic Differential scales

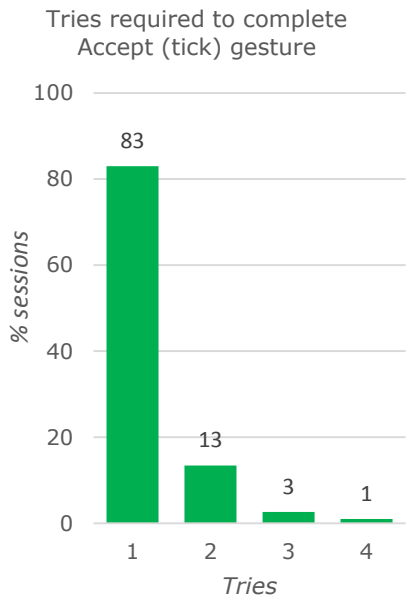
PROCEDURE

Participants completed a consent form, demographics, and an online questionnaire to measure pre-intervention specific and general attitudes using Lime Survey. Intervention participants installed the app and it ran for 2 weeks or 256 trials (replicated from Kakoschke et al. [2014]), whichever happened first. Control participants received no intervention. After 2 weeks, participants completed a post-test questionnaire identical to the pre-test. All intervention participants were invited to a post-intervention email interview; 6 accepted.

RESULTS

QUANTITATIVE-USAGE

Intervention participants completed 256 trials. On average, participants completed 232 healthy food-tick trials (SD=*6.27*) and 24 unhealthy food-cross trials (*SD*=6.27). Figure 5.5 and Figure 5.6 show the number of tries required to complete the required gesture, showing participants found it more difficult to perform the cross gesture correctly first time than the tick gesture. The mean error rate (where participants failed to perform the correct gesture 3 times in a row) was 1.31% (*SD* 1.04). On average, participants completed the 256 trials in 5 days (max=11, min=2), with an average number of trials per day of 51.



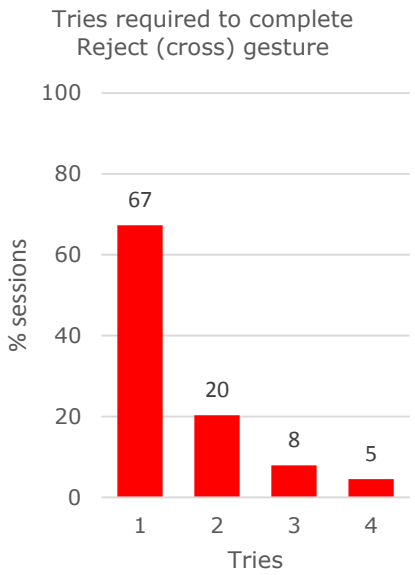


Figure 5.5 Accept (tick) gesture tries

Figure 5.6 Reject (cross) gesture tries

QUANTITATIVE-ATTITUDES

Our hypothesis was that the intervention would change specific and general attitudes towards healthy and unhealthy foods. Descriptive statistics for each measure (HTAS GHI, HTAS taste, HFA, UHFA, HFIR and UHFIR) are shown in Table 5:1. Table 5:2 shows 1 standard-error barplots for the measures. Table 5:3 summarises the outcome of mixed ANOVAs run on our 6 measures. Note that no family-wise Bonferroni error correction has been made to correct for our multiple hypothesis tests. This means that the two statistically significant results (p=.02 in both cases) may be false positives / Type 1 errors. The Bonferroni-corrected significance level for 18 comparisons at the 95% confidence level would be .0028 (=.05/18).

Measure	*Group*	*Mean*	*SD*
HTAS GHI	Control Pre	4.52	1.06
	Control Post	4.45	1.07
	Intervention Pre	4.23	0.76
	Intervention Post	4.81	0.75
HTAS taste	Control Pre	4.75	0.63
	Control Post	4.52	0.85
	Intervention Pre	4.59	0.68
	Intervention Post	4.34	0.55
HFIR	Control Pre	5.96	0.69
	Control Post	5.64	0.81
	Intervention Pre	5.73	0.42
	Intervention Post	5.64	0.85
UHFIR	Control Pre	5.24	1.09
	Control Post	5.22	0.73
	Intervention Pre	4.99	0.81
	Intervention Post	4.23	1.20
Attitude to healthy foods (HFA)	Control Pre	6.17	0.77
	Control Post	5.72	0.95
	Intervention Pre	6.21	0.45
	Intervention Post	6.18	0.59
Attitude to unhealthy foods (UHFA)	Control Pre	3.83	1.42
	Control Post	4.1	1.22
	Intervention Pre	3.86	1.09
	Intervention Post	3.49	1.00

Table 5:1 Descriptive statistics for food attitudes

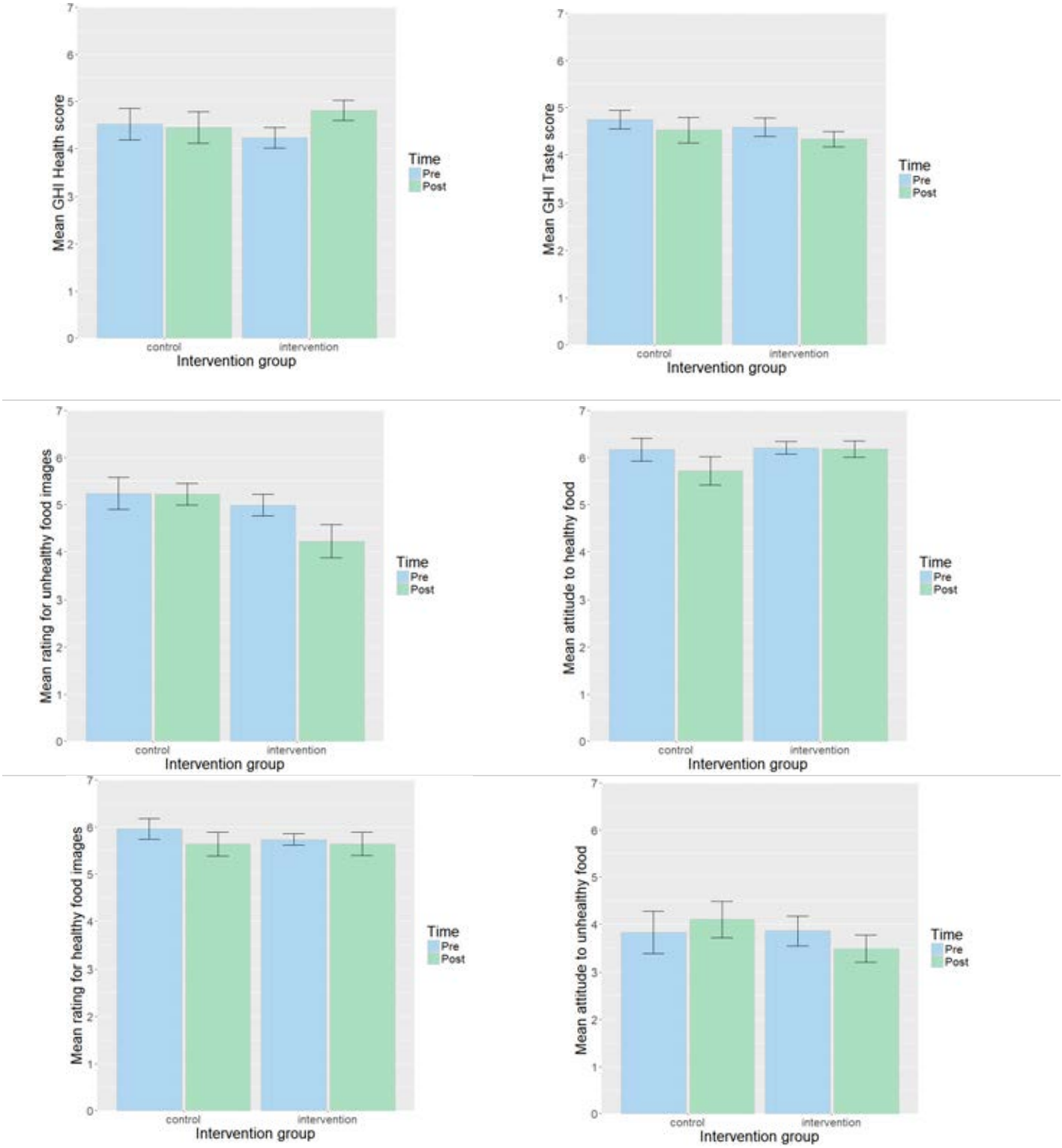


Table 5:2 Barplots with 1SE for food attitude measures

SPECIFIC MEASURES

Our two specific dependent variables were healthy food image ratings (HFIR) and unhealthy food image ratings (UHFIR). To test the hypothesis that our intervention would alter these measures, we ran a 2x2 (intervention group x session) mixed ANOVA on each variable (HFIR or UHFIR) with intervention group (control or intervention) as a between-subjects factor, and session (pre or post) as a within-subjects factor. There was no evidence for any main or interaction effects of intervention group and session on either HFIR or UHFIR, all p>.05, as shown in Table 5:3.

Dependent variable	*Levene's test*	*Shapiro-Wilk*	*2x2 Mixed ANOVA*	
		Specific measures		
HFIR	$F(3,40) = 0.92$ p=.44	All $p > .05$	Session Intervention Session x intervention	$F(1,20) = 1.32$, p=.26 $F(1,20) = 0.21$, p=.65 $F(1,20) = 0.40$, p=.53
UHFIR	$F(3,40) = 0.62$, p=.61	All $p > .05$	Session Intervention Session x intervention	$F(1,20) = 3.10$, p=.09 $F(1,20) = 3.00$, p=.10 $F(1,20) = 2.70$, p=.12
		General measures		
HTAS GHI	$F(3,40) = 1.75$, p =.17	All $p > .05$	Session Intervention Session x Intervention	$F(1,20) = 3.70$, p=.07 $F(1,20) = 0.01$, p=.93 $F(1, 20) = 6.21$, p=.02, η^2_p =.24
HTAS Taste	$F(3,40) = 1.11$, p= .36	All $p > .05$	Session Intervention Session x Intervention	$F(1,20) = 6.37$, p=.02, η^2_p =.24 $F(1,20) = 0.40$, p=.53 $F(1,20) = 0.03$, p=.87
Attitude to healthy foods (HFA)	$F(3,40) = 2.11$, p=.11	All $p > .05$	Session Intervention Session x intervention	$F(1,20) = 1.98$, p=.18 $F(1,20) = 1.06$, p=.31 $F(1,20) = 1.54$, p=.23
Attitude to unhealthy foods (UHFA)	$F(3,36) = 0.42$, p = .74*	All $p > .05$*	Session* Intervention* Session x intervention*	$F(1,18) = 0.02$, p=.89 $F(1,18) = 1.67$, p=.21 $F(1,18) = 3.04$, p=.10

** run on truncated data due to initial non-normal data*

Table 5:3 Analysis of attitude measures

GENERAL MEASURES

ATTITUDE SEMANTIC DIFFERENTIALS

We examined internal consistency for our two attitude measures; attitude to healthy foods (HFA) and attitude to unhealthy foods (UHFA). Internal consistency was good for HFA-Post (α = .78), UHFA-Pre (α=.74) and UHFA-Post (α=.79) semantic differentials, and acceptable for the HFA-Pre semantic differential (α = .60).

To test the hypotheses that our intervention altered HFA measures, we ran a 2x2 mixed-ANOVA on HFA with intervention group (control or intervention) as a between-subjects factor, and session (pre or post) as a within-subjects factor. The HFA analysis showed no evidence of any main or interaction effects (p >.05) as shown in Table 5:3, and therefore no evidence of an impact of the intervention. Attitude towards unhealthy food was not normal for one cell of the 2x2 intervention x session matrix (control Pre measure W=0.77, p = .01 for unhealthy attitude). We removed 2 outlying users to obtain non-significant Shapiro-Wilk tests (p > .05) and ran a 2x2 mixed ANOVA on UHFA with intervention group (control or intervention) as a between-subjects factor, and session (pre or post) as a within-subjects factor. The results showed no evidence of statistically significant effects (p>.05) as shown in Table 5:3 and therefore again no evidence of changes due to the intervention.

HTAS SCORES

To test the hypothesis that our intervention would alter the two HTAS scores (GHI and Taste), we ran a 2x2 mixed-ANOVA for each measure with intervention group (control or intervention) as a between-subjects factor, and session (pre or post) as a within-subjects factor.

HTAS GHI

There was a small statistically significant effect of the group and session interaction on the HTAS general health index (GHI) score, $F(1, 20) = 6.21$, p=.02, η^2_p=.24. Post-hoc Tukey-adjusted pairwise comparisons showed a statistically significant difference between intervention scores pre- (mean = 4.23) and post- (mean= 4.81) $t(20)$=3.28, p=.02, but no statistically significant difference between control scores pre (mean= 4.53) and post (mean=4.45), $t(20)$ = 0.38, p=.98. This effect is also shown in the plot of the model's estimated marginal means using the lsmeans package [Lenth 2016] shown in Figure 5.7. The figure indicates that the model predicts increased GHI scores for the intervention group, although the estimated marginal mean 95%CIs cross; note that estimated marginal means only model the fixed, not random, parts of the model.

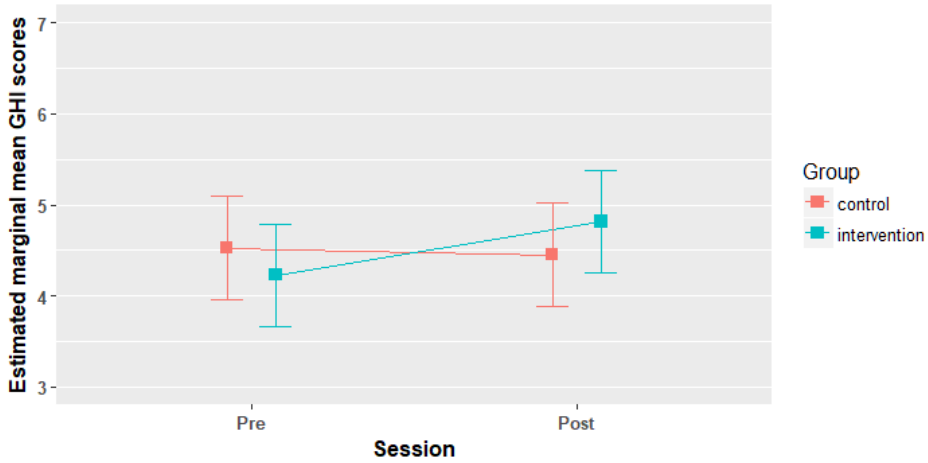


Figure 5.7 Estimated marginal means plot with 95%CIs for GHI by group and session

HTAS TASTE

As shown in Table 5:3, there was a statistically significant main effect of session on the HTAS Taste score $F(1,20) = 6.37$, $p=.02$, $\eta^2_p = .24$, but no main effect of group or group - session interaction (all $p>.05$). This effect was an overall decrease in HTAS taste scores of 0.24 between pre- and post-, regardless of group. This provides evidence of a general experiment effect, i.e. that mere participation reduced taste scores, rather than any evidence of an impact of the intervention as we hypothesised.

QUALITATIVE-INTERVIEWS

6 of the 12 intervention participants completed a brief semi-structured post-intervention interview via email. Responses indicated most felt the app had an impact on a conscious level: 5/6 felt the app supported them to make conscious healthy food choices e.g. *"[it] … help you to recognise the food that is bad for your health"* (P6). P3 felt the app was helpful because it provided reminders, while P1 felt the app could help to indicate which foods are healthy in the case of ambiguity e.g. yogurt. Others were more sceptical: "*I don't think that if you cross or check pictures you will change the food that you eat*" (P4); another thought that the intervention period was too short "*very little time using it*" (P3).

Requests for feature improvements included personalisation of healthy/unhealthy food (3 participants), with one participant not recognising avocados (P4), and another reporting frustration that the application didn't let them eat pizza" (P5). Two participants reported frustration with gesture recognition, particularly when in a hurry: "*when it is a rush, sometimes had to try it 2-3*

times" (P2). P2 was also frustrated by a double-unlock: first to perform the training, and second to enter their PIN.

DISCUSSION

Our hypothesis was that the intervention would alter specific and general food attitudes. The results only show some evidence that one measure of general attitude changed as a result of the intervention: there was a statistically significant interaction between session and intervention for the HTAS GHI score. There was also evidence of a statistically significant general drop in HTAS taste scores from pre- to post, regardless of intervention group, indicating that for all participants, their craving and focus on unhealthy foods dropped between sessions. No other evidence for changes was found, despite the larger proportion of healthy 'accept' trials completed, which we expected to impact on our specific measure of food attitudes, food image ratings, via the mere exposure effect [Zajonc 1968a]. Nevertheless, the HTAS GHI score questions are general rather than specific (e.g. "I always follow a healthy and balanced diet"), indicating that the intervention may have some generalised effects. However, caution is required to interpret these results since family-wise Bonferroni error corrections were not applied, increasing the likelihood of false positives.

LIMITATIONS

The results are limited by small sample size, small numbers of unhealthy trials, and the non-randomised allocation of intervention group. The allocation was not randomised due to small numbers of participants: all those with Android smartphones were invited to the intervention group. The control group did not install anything on their phone, so it is not possible to determine from this experiment whether it was the CBM training, rather than the presence of the unlock training screen providing simple reminders, that had an impact on GHI scores.

Contrary to expectations, we found no evidence of improvements of liking of the specific healthy foods used in the experiment, or a reduction in liking of unhealthy foods, as measured by users rating the food images used in the experiment. The measures were conducted in-the-wild, and we did not gather additional possible confound data such as user hunger or current levels of self-control resources. A measure of implicit food attitude may have yielded different results. With the general measures, the semantic differentials were a relatively small set, and could have included measures of more rigorous underlying concepts instead of including the somewhat tautologous "health-unhealthy" dimension.

Looking at Table 5:2, if we consider 95% confidence intervals of approximately 2 times the standard error, it's clear that some of the procedures we used could not easily detect a change in attitudes. For example, for ratings of healthy food (attitude to healthy food, rating for healthy food images), at the outset mean ratings exceeded 5.5 (out of 7). Given the unlikelihood of participants scoring the maximum for any given measure, the standard error and thus confidence intervals would need to be much reduced (e.g. by increasing *n* as discussed on page 4:61) in order to detect the expected small increases in these measures. Again, given the evidence from psychology that CBM techniques can be successful, we consider that CBM is still a potential strategy for further investigation. However, we suggest that future interventions restrict measurement to the validated GHI scales, alongside other strategies to increase power.

The data shows a variation in the number of days taken to complete the 256 trials –maximum 11 days, minimum 2 days. Our follow-up measures were all taken 14 days after the start of the intervention. It may be that the CBM training should be undertaken in a more concentrated period of time in order to be effective. Further, the *physical* push/pull effort in the CBM-Ap paradigm may be important: future work could explore the use of motion gestures to accept/reject stimuli. Task-based training of larger physical push/pull gestures is the focus of Study 6.3.

Study 5.2: Follow-Up Qualitative survey

Overview

To broaden our understanding of the domains in which end-users might want to use cognitive bias modification technology, we conducted an online survey. These questions ran alongside those in survey 4.2. 145 participants completed the survey (age mean 30.3, *SD* 11.86, 106 women). 56% were students. 137 of these also completed survey 4.2. After answering the 4.2 questions, participants were briefly informed about CBM-Ap training, i.e. the repeated acceptance or rejection of particular trigger items, and asked to nominate their own accept/reject pairs. Examples of rejecting cigarettes and accepting chewing gum, and choosing celery and ignoring chocolate biscuits were given.

Results

Responses were analysed using iterative content analysis. Table 5:4 shows themes, specific items and accept/reject pairs reported.

Theme	*Mentions*	*%*	*Item*	*Mentions*	*%*	*Pairs*	*Mentions*	*%*
Food	81	56	Fruit	51+	35	Chocolate-fruit	28	19
Exercise	69	48	Chocolate	41*	28	Soft drink-water	21	14
Technology^	56	39	Water	39+	27	Junk food-healthy food	13	9
Drink	52	36	Book	32+	22	Smartphone-book	11	8
Reading	35	24	TV	25	17	TV-exercise	10	7
Sedentary behaviour	33	23	Phone	19*	13	TV-book	8	6
Study/work	15	10	Sofa	17*	12	Sweets-fruit	8	6
Sleep	13	9	Trainers	13+	9	Technology-outdoors	8	6
Smoking	4	3	Computer	8+*	6	Biscuits-fruit	6	4
Posture	4	3	Wine	8*	6	Alcohol-water	6	4

** Reject item*

+Accept item

^Technology includes TV, mobile phones, tablets and computers. 1 mention was Accept technology; the rest were Reject.

Table 5:4 Top Theme, Item and Pairs mentioned for Accept/Reject CBM behaviour change

Key survey themes

DOMAINS

The top 3 domains of interest were food, exercise and technology. Users wish to alter food and drink intake, levels of activity and usage of technology. Items results show chocolate and TV as the highest-mentioned reject items; fruits and water were the highest-mentioned accept items. Reflecting the theme results, people suggested healthy-unhealthy food and drink items most frequently, and alternatives to technology (TV, phones, desktops, laptops, tablets), which included books, exercise and the outdoors.

Since we investigated food issues in Study 5.1, and address exercise further in Chapters 6 and 7, here we focus on the emerging issue of problematic technology use.

PROBLEMATIC TECHNOLOGY USE

This theme encapsulates concern over overuse of technology. 18 participants (12%) wanted to swap their TV for either exercise or reading. Of 19 mentions of problematic phone use, the majority (58%) wanted to substitute their phone for books. In terms of motivation to reduce use of technology, participants identified a link between phone usage and sleep: "m*y sleep could also be improved so*

maybe cutting back on using my phone … could help" (P48); and between phone usage and lack of productivity: "*I often get distracted from studying by my phone*" (P65). 5% of respondents were sceptical about using a phone as anti-phone training; "*want to get away from technology*" (P7); "*playing with my phone is a habit I haven't really got into yet so don't want my retraining to come via phone*" (P98). We explore this theme further in study 5.3.

PROBLEMATIC AUTOMATICITY

89% of participants reported awareness of making unhealthy choices, e.g. "*I should be doing more of the good things and at present I'm too prone to doing the bad ones*" (P34), with 15% reported issues with controlling themselves, e.g. "*I feel like I go to [Facebook] almost instinctively when I don't know what I want to do*" (P44); "*They are choices I frequently regret after I've made them, and always resolve to do differently the next day*" (P9). 3% reported issues with low motivation, and the same number with being unable to resist temptations.

REACTANCE

Several participants (10%) identified potential reactance in engaging with opportunistic CBM systems, e.g. "*the risk is it becomes annoying … they only work short term and only when you are not busy*" (P13). 5% of participants also identified ironic effects: "*pictures of food will only remind me of food and make me feel hungry*" (P139).

DISCUSSION & LIMITATIONS

The survey showed people are concerned about healthy eating, exercise and technology overuse, although we note that to aid user understanding of our questions, we also gave some concrete examples (smoking; eating) which may have biased responses.

There is evidence that people are aware of unhealthy choices, with some identifying automaticity as a possible cause. Some respondents were sceptical about the long-term impact of incidental CBM interactions. People reported possible ironic effects, reactance, and a dislike of using their smartphones for such training. This led us to shift research focus away from potentially irritating at-unlock opportunistic CBM training to focus instead on a training task-based CBM delivered at a larger scale on a Tabletop Surface, the subject of Experiment 5.3.

Experiment 5.3: "Push away the smartphone"

This study was carried out as part of a student project by Jose Ignacio Rocca.

Motivation

Within our RQ2, "how can technology best exploit opportunities to intervene in a user-friendly way", we wanted to explore how CBM-Ap might be used to counter problematic smartphone usage. Problematic technology use was in the top 3 user domains of concern in Survey 5.2, is a domain in which the problematic cue is clearly identifiable, and one in which participants reported problematic automaticity. We therefore explored whether training on a Tabletop with push and pull Cognitive Bias Modification training might enable our participants to overcome this. We anticipate a growing demand for counter-smartphone measures given evidence of ever-increasing smartphone sales [Gartner 2018] and evidence that problematic use interferes with everyday life [van Deursen et al. 2015; Wolniewicz et al. 2017; World Health Organization 2014].

Survey 5.2 indicated that 39% of users were concerned about overuse of their technology. 13% specifically mentioned rejecting their smartphones, and 8% suggested a smartphone-book push/pull pairing. Our intervention platform was a Tabletop, building on the possibility that the *physical* push/pull gesture is important in CBM-Ap, and survey 5.2 evidence that people did not want to perform anti-smartphone training on their smartphones. We used reaction time as a dependent variable, rather than a measure of self-reported attitude as in Experiment 5.1. Using a Tabletop also gave us more control than the in-the-wild experiment 5.1.

Introduction

Tabletop interventions

The Tabletop allows people to make more expansive accept/reject push/pull gestures than on smartphones. It also allows the emulation of more realistic situations in which a person might wish to "push away" a smartphone, and avoids delivering an anti-smartphone training on a smartphone. Tabletops have been used to support individual and collaborative activities in multiple domains, including design [Rick et al. 2009], tourism [Marshall et al. 2011] and games [Piper et al. 2006]. However, it is still not clear which applications Tabletops are best suited for [Wallace et al. 2017]. This study explores whether CBM-Ap applications, yet to be explored on Tabletops, are a good fit.

SMARTPHONE ADDICTION

Smartphone usage is pervasive, with ownership at 69% in the UK in 2015 [Ipsos 2015]. Worldwide mobile phone shipments reached 1.86 billion in 2017, and are predicted to rise into 2018-9 [Gartner 2018]. Meanwhile, concern over problematic usage of smartphones is growing. Research into the effects of problematic usage of smartphones is still at an early stage [Wilmer et al. 2017], since platform innovation tends to outpace research, but indicates possible impacts on psychological wellbeing [Samaha and Hawi 2016] and depression [Elhai et al. 2017a]. Night-time use disrupting sleep is a particular issue [Vernon et al. 2018]; the World Health Organization suggests that "excessive use of smartphones and electronic screen products relates to sleep deprivation" [World Health Organization 2014].

Problematic usage may emerge where smartphone use develops into a habit, because habitual behaviours are automatic and beyond conscious control [Oulasvirta et al. 2012]. Initial drivers that prompt usage that evolves into problematic behaviour may initially be social (e.g. to keep in contact with friends) or process (e.g. to read news or listen to music) [van Deursen et al. 2015; Elhai et al. 2017b]. Habitual usage can lead to excessive phone checking, which can interfere with everyday life when people experience unwanted impulses to check their devices [van Deursen et al. 2015; Wolniewicz et al. 2017]. Problematic use may also make driving more dangerous and induce antisocial behaviour [Kuss et al. 2018].

METHOD

This experiment applied the principles of CBM-Ap training to a Tabletop, using smartphones as the 'avoid' stimuli and books as the alternative 'approach' stimuli. This experiment was adapted from the Wiers et al. alcohol approach-avoidance task (AAT) [2011] detailed in Chapters 3 and 5, where heavy drinkers initially showed an approach bias to alcohol pictures, which reverted to a small avoid bias on training.

DESIGN

There were two experimental phases (i) testing smartphone addiction using a survey on a laptop and (ii) interacting on the table for pre- and post- CBM-Ap measurement. The intervention group additionally completed a training task after the pre-CBM-Ap measurement. To test our hypothesis that our intervention would alter smartphone response times, we used a pre-test/post-test control group design. Our independent variables were intervention group (control and intervention,

between-subjects) and session (pre- and post-, within-subjects) Our dependent variable was a measure of approach bias derived from time taken for participants to complete the task. We used reaction time as a dependent variable rather than a measure of self-reported attitude as in previous experiments to counter issues of inaccurate self-report in the face of automatic behaviours, since they are not accessible to conscious reflective processes [Hagger et al. 2015]. We used a measure of smartphone addiction as a continuous predictor.

Hypothesis

We hypothesised that there would be a statistically significant interaction between intervention group and session. We predict that, when compared to the control group, participants in the intervention group will show decreased smartphone approach bias score at post-test compared to pre-test measures.

Participants

40 people participated (age: mean=26.9, SD=4.17; 12 women), 20 in each group. They were recruited via email and text message.

Measures

Smartphone approach bias measure: to measure CBM-Ap, we recorded reaction times for participants to complete either a push (reject) or pull (accept) action for each smartphone stimulus on the Tabletop, measured from the time the stimulus appeared to the time at which the stimulus reached a target area. We calculated smartphone approach bias scores by using the difference in reaction times for pull and push stimuli, divided by each user's standard deviation, following Wiers et al. [Wiers et al. 2011].

Smartphone addiction: we used Kwon et al.s' 10-point shortened Smartphone Addiction Scale (SAS-SV) with a 6-point Likert scale [2013] as a measure of smartphone addiction. We chose the SAS-SV because it has high internal consistency ($\alpha = 0.91$) and validity with respect to longer versions [Kwon et al. 2013], and has been validated in related research [Haug et al. 2015; Hawi and Samaha 2016].

Task

Participants were tasked with a series of trials to accept or reject stimuli. To accept the stimulus the participant had to *pull* the stimulus towards them into a rectangular target area. To reject the

stimulus the participant had to *push* the stimulus away from them into a different rectangular target area on the opposite side of the Tabletop. The interface is shown in Figure 5.8.

Each trial consisted of a stimulus appearing in the centre of the table, surrounded by a landscape, portrait or (for training intervention participants only) square frame. All participants completed a practice session (10 trials), and two measurement sessions (pre and post). Measurement consisted of 40 trials with equal numbers of smartphone and book stimuli. Reaction time data from responses to smartphone stimuli were used to derive our measure of smartphone approach bias. For practice and measurement trials, participants were asked to respond to the frame shape by pushing landscape frames and pulling portrait frames as shown in Figure 5.8.

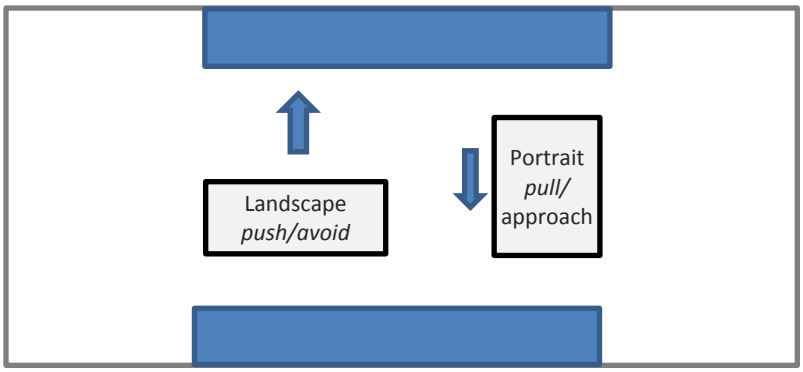


Figure 5.8 Stylised layout showing approach and avoid areas on Tabletop

Intervention participants additionally completed 60 training trials in between the pre- and post-measurement sessions. The intervention task was to push away images of smartphones and pull towards them images of books. Each training stimulus had a square outline to differentiate them from the landscape/portrait pull/push.

Trials were conducted on a Microsoft Pixelsense SUR40 (Microsoft Surface), a 40-inch multi top Tabletop in the lab. We included target goal areas for “push” and “pull” trials to ensure participants completed a gesture directly towards/away from themselves and not, for example, into a corner of the screen.

Stimuli were presented in a random order with no restriction on similarity with previous trial. Participants were encouraged to take a small rest between sessions to alleviate fatigue.

Stimuli

Practice session stimuli were grey triangles within the landscape or portrait frames. Stimuli for pre- and post-test measures and intervention trials were smartphones and book covers. To match the smartphone stimuli with participants' own phones, we asked participants to choose the smartphone that most closely resembled their own from a range of 10. We then used images similar to their selection as smartphone stimuli, although image restrictions meant numbers of stimuli for each smartphone model ranged from 3 to 8. For the book cover counter-stimuli, we used 52 images of book covers, displayed randomly.

Pre- and post-test measures (40 trials) included equal numbers of book and smartphone stimuli, with equal numbers of push and pull tasks for each, as indicated by either landscape or portrait frames.

Intervention groups

Participants were assigned to either the intervention or the control groups, balanced for smartphone addiction score. Participants in the intervention group performed a series of 60 training trials, as outlined above, while control participants received no training. This was in line with Wiers et al.'s finding of no statistically significant difference between control no-training vs control sham-training conditions [Wiers et al. 2011].

Procedure

Participants attended a session in a common room in the University of Birmingham's Computer Science building. They completed a consent form, demographics and the SAS-SV measure of smartphone addiction on a laptop. Participants then moved to the Tabletop and completed the task according to intervention group. The Tabletop training in action is shown in Figure 5.9. Participants stood near the 'accept' area.

Figure 5.9 The application in use: a user pushes away a phone

All participants completed the same practice and pre- and post- measurement procedure, while the intervention group completed an additional training set of trials in between pre- and post-measurement trials. The experiment procedure summarised in Table 5:5.

Group	*Control*	*Intervention*	*Protocol*
Practice	10 trials, grey rectangles		Format training Pull portrait (5); push landscape (5)
Pre-measure of approach/avoid bias	40 trials		Equal numbers of books and phones; equal numbers of push and pull for each
Intervention	No trials	60 trials	Equal numbers of books and phones; all square format; phones all "push" and books all "pull"
Post-measure of approach/avoid bias	40 trials		Equal numbers of books and phones; equal numbers of push and pull for each

Table 5:5 Experiment procedure

RESULTS

SMARTPHONE ADDICTION

Participants reported spending an average of 4.93 hours a day on their smartphones (*SD*=3.97). They reported checking their smartphones on average 54 times a day (*SD*=45.4). In response to the question "Do you think you have a maladaptive dependency or addiction over your smartphone usage?", 17 (42.5%) said yes, 16 (40%) said no and 7 (17.5%) said "I don't know".

Descriptive statistics for raw SAS-SV scores are shown in Figure 5.10.

Group	*Mean*	*SD*
Intervention	30.11	7.84
Control	31.95	8.42

Figure 5.10 Raw SAS-SV scores by intervention group

Unlike in the original scale validation tests [Kwon et al. 2013], we found no evidence that SAS-SV score differed by gender (Welch t-test $t(19.4)=0.33$, $p=.75$, mean difference = 0.96, 95% CI[-5.14, 7.07], Cohen's $d=0.12$). We also found no evidence of a statistically significant difference in SAS-SV scores between intervention group (mean= 30.1) and control group (mean=32.0); Welch t-test $t(37.96) = 0.71$, $p=.48$, 95% CI[-3.36, 7.05], Cohen's $d=0.23$. This is shown in Figure 5.11. Figure 5.11 also shows that smartphone addiction scores broadly follow self-categorisation of smartphone addiction (No, Don't know and Yes categories).

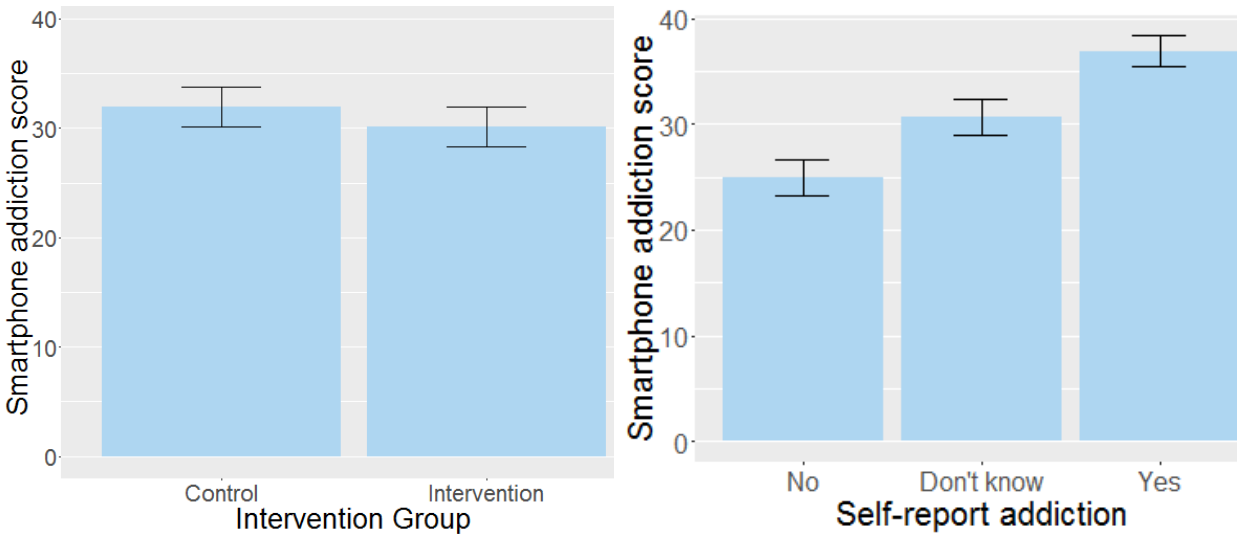


Figure 5.11 Barplot of mean smartphone addiction scores (SAS-SV) with 1 Standard Error (SE) error bars by (left) intervention group and (right) self-categorised addiction

Effect of training

From 1,600 pre- and post- trials with smartphone stimuli, we removed 29 (1.8%) error trials, 12 trials where reaction time exceeded 5 seconds (0.75%), and 186 trails (11.63%) where reaction time was less than 1 second after visual inspection showed a clear separation of reaction times around the 1s mark (see Figure 5.12).

This data observation reflected an experimental observation that some participants learned that they did not have to complete the full-arm action to move the stimuli from the starting position to the target; instead they completed the move with a 'flick'.

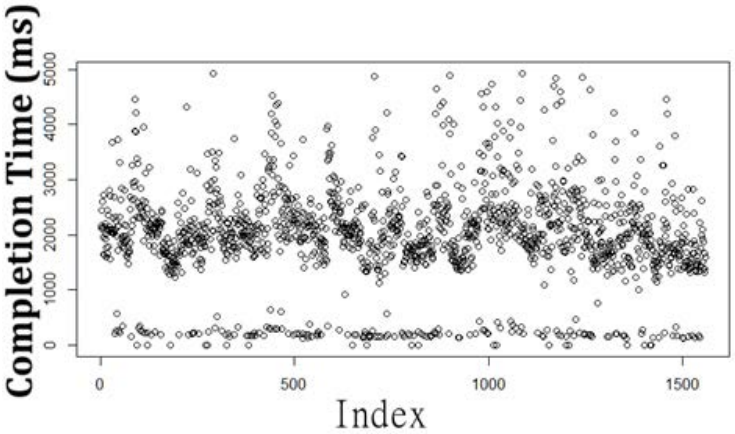


Figure 5.12 Raw completion time data

Figure 5.13 shows the Smartphone Approach Bias scores by session and intervention group.

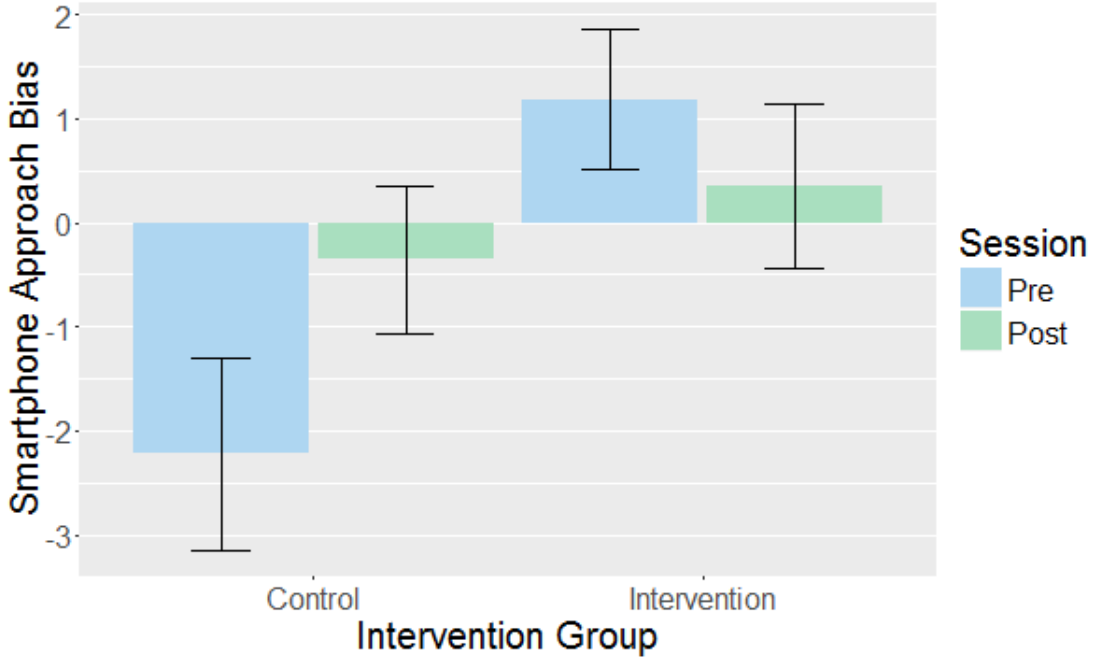


Figure 5.13 Smartphone approach bias score barplot with 1SE error bars

To investigate our hypothesis that the intervention group would alter smartphone approach bias after training, with differing effects depending on smartphone addiction score, we used a LMER model. Our model examined the effect of intervention group (control vs intervention, control as

baseline), session (Pre vs Post, Pre as baseline), and smartphone addiction (measured by SAS-SV as a continuous covariate) on the smartphone approach bias measure. It included a by-participant random intercept.

The model results (R2ps=0.42) are shown in Table 5.6. Note that the p values are not Bonferroni-corrected. The Bonferroni corrected significance level for 8 comparisons at the 95% confidence level would be .0063 (=.05/8).

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. The 3-way Group:Session:SAS-SV interaction not statistically significant p = .27.

Fixed effects	*Estimate*	*SE*	*t*	*p value*
(Intercept)	-2.44	0.74	-3.28	.002
Group	3.53	1.08	3.27	.002
Session	1.98	0.98	2.01	.05
SAS-SV	0.25	0.09	2.73	.008
Group:Session	-2.74	1.43	-1.92	.07
Group:SAS-SV	-0.34	0.14	-2.52	.014
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			

Model formula: bias score ~ group * session * SAS-SV + (1|participant)

Table 5:6 Smartphone approach bias model analysis results

The highest-level statistically significant result was a 2-way 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 was lower for intervention participants compared to control participants.

This effect is shown in Figure 5.14, which plots fitted model values for smartphone approach bias against smartphone addiction score for our two participant groups.

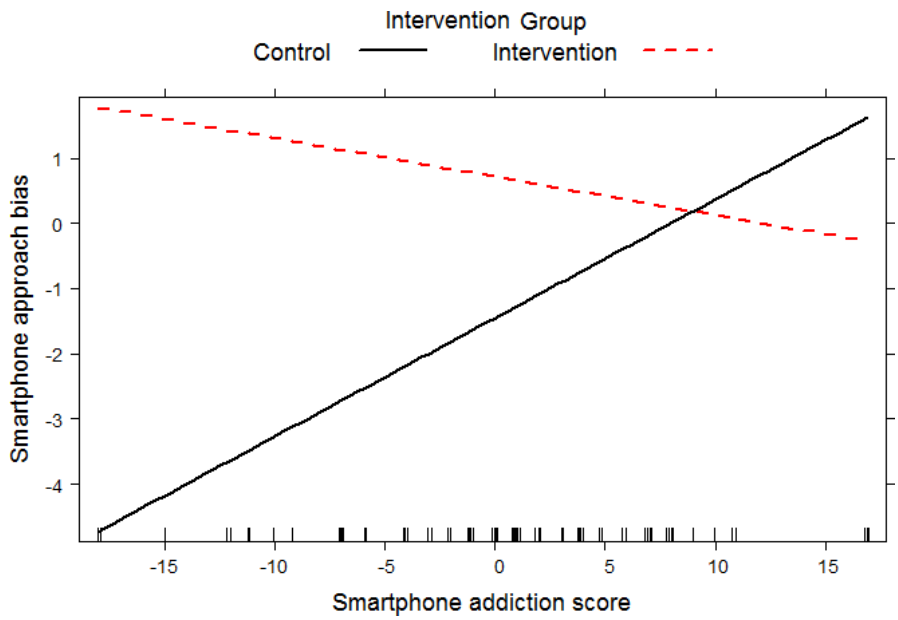


Figure 5.14 Effect plot for smartphone approach bias and smartphone addiction score across intervention groups

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 would be expected to show positive smartphone approach biases at the outset, which we hypothesised would be moderated by the training in intervention participants.

We found a 2-way statistically significant interaction between smartphone addiction score and intervention group, although this was not significant at Bonferroni-corrected *p* values. The effects plot showed that the interaction of smartphone addiction score on smartphone approach bias differed between our intervention group participants. Although for both groups, a high-addiction score was associated with high-approach bias scores, the converse was only true for the control 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.

If the SAS-SV measure of smartphone addiction is a true measure of underlying issues with smartphones, it appears that this was not manifested consistently in the expected CBM-Approach bias in our experiment, i.e. that the problematic stimulus (the smartphone) triggers an automatic approach response.

LIMITATIONS

Our reaction time data was from a relatively small sample (n=40) and was noisy, and our residual measure of random effects was high within our data model relative to the effects explained by random variation per user. One source of noise was the semi-controlled nature of the experiment: the Tabletop was in a social space within the Computer Science department, with no restrictions on distractions. Re-running the study in a more controlled environment with a larger n and interaction shortcuts disabled would help to disambiguate the statistically non-significant results.

Note from Figure 5.13 that the experiment may not have had sufficient power to detect small improvements in our measure of bias. In the context of confidence intervals approximately twice those of the 1 standard error bars shown (see p 4:61), the experiment would only detect a difference of around 3 points on the bias score. In terms of our RQ2, we have found no evidence that a Tabletop CBM intervention is an appropriate way to support people wishing to reduce smartphone addiction, either in terms of user-friendliness (given the high data variability and levels of circumventing the training) or effectiveness. Nevertheless, CBM remains a valid NDBCI given the evidence of its effectiveness from psychology labs; we return to its potential in Chapters 7 and 8.

Although our experiment was based on Wiers et al. [2011], who used an approach-avoid task as both intervention and measure, there were some important differences. Firstly, we used a smaller number of testing and training trials (testing – us: 40 trials, Wiers et al., 80 trials; training – us: 60 vs Wiers at al.s' 440), because of the risk of user fatigue and boredom. Secondly, we used the same randomised stimuli throughout, rather than using a mix of trained and untrained stimuli in the post-test phase to check for effect generalisability. Images of smartphones are much more similar to each other than images of different types of drinks; checking for generalisability would therefore be difficult even if we used untrained images of smartphones. Thirdly, our participants used different physical gestures – full-arm push and pull – rather than the Wiers et al. joystick with similar amounts of movement for a push/pull gesture. It may be that any underlying CBM-Approach bias is not accurately captured by a 'pull' gesture.

Lastly, smartphone users re-train themselves to approach their phones through ordinary smartphone usage, undermining training interventions. Our intervention required a larger physical movement to 'reject' and 'accept' items than either the previous study on smartphones (5.1) or lab joystick movements, and allowed us to replicate a more lifelike situation in which a participant might encounter smartphones. However, this intervention may be insufficient to counter ingrained smartphone-approach behaviour in-the-wild unless it is repeated frequently. Given that Tabletops are not generally available, this is unlikely. Intervention participants also completed an intervention task, whilst the control participants did not, which may have impacted on post-intervention reaction times through fatigue.

Summary

This chapter explored the application of CBM as a nonconscious intervention technique in two different formats and two different experimental contexts. We implemented an incidental CBM intervention in-the-wild on smartphones in the healthy eating domain, and a semi-controlled training task CBM intervention on Tabletops in the domain of problematic smartphone usage.

We wished to assess CBM's suitability as a nonconscious intervention technique in in-the-wild and semi-controlled conditions. Trial error rates were low (coincidentally 1.31% for both studies) indicating that participants found it relatively easy to comply with the specific task. However, our results highlight several difficulties in translating CBM techniques into spaces where users carry out their daily lives. We found some evidence from Experiment 5.1 that the intervention altered some general attitudes towards healthy food, although not at a Bonferroni-corrected level of significance. However, with no evidence of any accompanying shifts in specific attitudes, it is difficult to determine whether this was due to the incidental training, by participants being reminded to consciously consider healthy food choices by the training, by participants being nonconsciously primed by the training, or whether the statistically significant results were a false positive. We also note that our healthy food ratings had limited power to detect changes. Participants also completed the task in different time frames – from 11 days to 2 days. Experiment 5.3 tried to counter this problem by using reaction times as a proxy for attitude and using a single, focused training task in semi-controlled conditions. Again, although there was some evidence of statistically significant differences in approach bias, they were not related to session and therefore our intervention.

CBM remains a candidate intervention paradigm for NDBCIs because of their evidence of efficacy from psychology. However, we have yet to show strong evidence of its impact in our small in-the-

wild and semi-controlled experiments. In terms of our RQ2, “how can technology best exploit nonconscious opportunities to intervene in a user-friendly way”, we have found user interest in the technique in a broad range of domains including food, exercise and technology. However, we also found some evidence that our approaches were not overly user-friendly. Study 5.1 showed that whilst it is possible to apply lightweight CBM training to incidental interactions, there is a risk of user irritation if it is not embedded fully as part of existing interaction. For example, where users had a number unlock in place, they had to complete 2 unlocks, and the gesture recognition was not always perceived as accurate. We also found no evidence of a change in food attitudes, and we note that our experiment was not able to detect small changes in scales due to its design and our data variability. Study 5.3 showed similar levels of data noise, with our data model showing relatively high levels of residual random noise after accounting for individual variation, and evidence of participants circumventing the training, with 12% of trials not employing the full drag-and-drop.

Therefore, we suggest that a more promising avenue of CBM training is to attach more seamlessly to incidental tasks, such as swiping between images in a gallery or changing television channels. Delivering this as individualised training may be a fruitful avenue of future research, with n-of-1 trials where participants can specify their own preferred CBM stimuli and mode of intervention [McDonald et al. 2017]. There remain interesting avenues of research in using CBMs in NDBCIs, which we return to further in Chapters 7 & 8.

Overall, within CBM studies, it is difficult to determine whether the training might have nonconscious impact, or whether the conscious attention required to complete the task might shift reaction times via explicit attitude. It is therefore difficult for us to disambiguate the lack of results for our experiments. In both experiments 5.1 and 5.3, participants in the intervention received instructions to explicitly accept or reject specific objects. They were asked to focus on the content of the images rather than the orientation, as in other lab studies which concealed the explicit purpose of the training. We reasoned that if this sort of CBM intervention were to be deployed, then both for ethical and motivational reasons, participants would be fully briefed on its purpose. Therefore testing with informed users reflects the most-likely future use case. However, using informed testing makes the results more difficult to interpret with respect to the conscious/nonconscious divide.

Therefore, our next research focused on a strategy that explicitly aims to disambiguate the conscious/nonconscious divide: subliminal priming. Subliminal priming is a method that does not consume deliberative cognitive resources. If a prime is subliminal, then it cannot be consciously recalled, so such primes are therefore less likely to trigger reactance since behavioural freedom is not

consciously perceived to be threatened. This also enables us to avoid context-detection issues; if the prime is not consciously perceived, then it should not matter if it is delivered at an inconvenient or incorrect moment. Nevertheless, there are many open research questions around how best to translate subliminal priming onto personal technology such as smartphones to be effective as a NDBCI strategy; this is the focus of the next chapter.

6. SUBLIMINAL PRIMING ON SMARTPHONES

This chapter addresses two broad questions: firstly, is subliminal priming possible on smartphones; and secondly, how might researchers apply the technique to nonconscious interventions? It discusses technical, ethical and design issues in delivering mobile subliminal priming. It presents four explorations of the technique: a technical feasibility study, and three participant studies:

- Study 6.1, a pilot (n=34) to explore subliminal goal priming in-the-wild over 1 week;
- Study 6.2, a technical feasibility experiment exploring the boundaries of timing issues on smartphones in the context of subliminal priming
- Study 6.3, a semi-controlled study (n=101) exploring the immediate effect of subliminal priming on 3 different types of stimuli, together with a further follow-up study (6.3B, n = 50) which investigated variations of stimuli and masks for the same purpose;
- Study 6.4, a semi-controlled study (n = 103) exploring semantic subliminal number priming on smartphones.

An MSc student, Po-Wei Chen, carried out data-gathering only for experiments 6.3.B and 6.4.

Motivation

We wished to explore the impact of an intervention strategy that unambiguously targets the nonconscious: subliminal priming. It has the potential to influence people's attitudes and behaviour, making them prefer certain choices over others. With respect to the BAF, it focuses on providing triggers via Type 1 attention and memory processes to generate the required impulses on the Potential Response stack. As we identified in Chapter 3, there is a research gap in exploring the application of subliminal techniques on smartphones and related design, ethical, user acceptance and technical challenges.

Little research has explored the feasibility of subliminal priming on smartphones, despite them offering multiple opportunities for priming, with an average of 5-105 uses [Truong et al. 2014], or 5 hours use [Andrews et al. 2015] per day. Some of these uses may be habitual [van Deursen et al. 2015; Oulasvirta et al. 2012], i.e. proceeding without conscious operation. This gives the opportunity to intervene without attracting conscious attention and risking disruption and/or reactance. Yet despite high smartphone ownership [Ipsos 2015] and many successful subliminal priming experiments in psychology labs, to our knowledge this is the first research to analyse the technique on mobile platforms. Replicating subliminal experiments on smartphones may yield different results

to those run in psychology labs since research shows replication is sensitive to contextual factors [Van Bavel et al. 2016].

This chapter explores the boundaries of subliminal priming on smartphones through a pilot, a technical feasibility study and 2 semi-controlled studies. *Subliminal priming* is the showing of a stimulus that has some effect without the participant having conscious recall of the stimulus [Bornstein and Pittman 1992; Merikle et al. 2001]. *Subliminal goal priming* is showing people stimuli to increase the likelihood of the goal-orientated behaviour [Pinder et al. 2015b; Shalev and Bargh 2011; Wood and Neal 2007]. Our particular interest is in the use of subliminal priming techniques in nonconscious behaviour change technology [Pinder et al. 2015a; Pinder et al. 2015b; Riener and Thaller 2014; Barral et al. 2014].

Theoretical Background

Dual process theories (DPT, see Evans [2008] for a review) help to explain subliminal priming. Subliminal priming techniques aim to covertly trigger automatic responses in the nonconscious system [Negri et al. 2014]. The advantage of subliminal instead of supraliminal triggers are that they can support people during tasks with high load on the conscious system [Wallace et al. 1991], potentially avoid irritation [Ham and Midden 2010], be less likely to promote behaviour that is in contrast with the prime [Glaser and Kihlstrom 2005], and can increase authenticity in responses [Shalev and Bargh 2011].

Mechanisms of subliminal priming

Subliminal priming aims to activate cognitive representations of stimuli outside of conscious attention [Macmillan 1986; Negri et al. 2014]. Subliminal goal priming tries to make it more likely an individual will perform a behaviour in line with a given goal. For this to work, the individual must have a pre-existing associative network of cognitive constructs related to the goal, including the means to achieve it. Priming re-activates this network, increasing its accessibility, making goal-related behaviour more likely [Aarts and Dijksterhuis 2000; Bargh et al. 2001; Custers and Aarts 2007].

Priming may also increase a goal construct's reward value via the mere exposure effect [Bornstein et al. 1987; Kunst-Wilson and Zajonc 1980; Custers and Aarts 2007]. The mere exposure effect is where exposure to stimuli increases subsequent liking judgements [Zajonc 1968b]. This effect has been extended into the subliminal, i.e. experiments where participants tend to prefer the stimuli they've

been shown, despite not being able to consciously recall seeing them [Seamon et al. 1984]. Monahan et al. [Monahan et al. 2000] found that the effect of *subliminal* mere exposure (SME) effects further increased with the number of exposures of a stimulus.

A second approach to increasing liking via priming (affective priming) is subliminal affective conditioning. This technique pairs a target item with a valenced (positive or negative) affective subliminal prime to alter participant attitudes and/or behaviour towards the target [Dijksterhuis 2004; Winkielman et al. 1997]. Dijksterhuis found that participants exposed to a ~17ms exposure of the word "I" alongside a positive trait showed an improvement in levels of self-esteem compared to a control group [Dijksterhuis 2004].

An additional important question is whether subliminal effects are due to a simple associative stimulus-response effect, or whether some deeper semantic processing can occur below conscious attention. The effectiveness of subliminal goal priming depends on semantic processing, i.e. activation of the goal-related associative network. Several researchers have found evidence of subliminal semantic processing [Naccache and Dehaene 2001; Ocampo 2015]. We address this question in section 6.4. With reference to the BAF, subliminal semantic priming should in theory both add stimulus-related impulses to the Potential Behaviour stack, and increase the implicit value of those impulses on the stack.

Subliminal HCI research

In HCI, subliminal experiments have primarily focused on enhancing "just-in-time" decision making. Experiments have investigated domains including visual search tasks [Aranyi et al. 2014; Pfleging et al. 2013], performance support in 3D intelligent tutoring systems [Chalfoun and Frasson 2011], memory support [DeVaul et al. 2003] and driving assistance [Riener and Thaller 2014]. Aranyi et al. [2014] found some evidence that subliminal cues can support selection tasks in virtual environments, but found only larger effect sizes for trials with fast response rates (≤1 second).

Subliminal scepticism

Researchers have expressed scepticism about both subliminal perception and subliminal priming [Pratkanis 1992; Moore 1988], partly due to lack of replicability and the weakness of the effect [Greenwald and Draine 1997; Greenwald et al. 1996]. The existence of subliminal *perception* is less controversial since neuroimaging techniques have shown activation in reward areas of the brain in response to subliminal presentation of meaningful stimuli [Pessiglione et al. 2007; Wetherill et al.

2014]. However, subliminal *priming* remains controversial, with ongoing discussions including how to demonstrate a lack of awareness of stimuli, methodological issues and how to establish reliable and replicable subliminal priming experiments [Draine and Greenwald 1998; Greenwald and Draine 1997; Shanks et al. 2013; Cheesman and Merikle 1984].

The technique is not universally accepted as effective in HCI: Pfleging et al. [2013] found no evidence that subliminal cueing on desktops can improve visual search tasks, compared to supraliminal cues, despite tailoring subliminal cue presentation to individual participants' perception thresholds. Similarly, Riener & Thaller's research [Riener and Thaller 2014] into the effect of subliminal lane change requests on steering behaviour found no statistically significant effects compared to a control group.

Design considerations

Prime Modality

Riener et al. [2011] identified four possible channels of subliminal communication: visual; auditory; olfactory and tactile. We selected visual as the most suitable channel for research on smartphones: auditory signals may not be attended to and phone sounds are often disabled; there are few tactile opportunities on a static touchscreen; and research into olfactory HCI on smartphones is in its infancy [Le Laboratoire 2015].

Stimuli Type

Visual stimuli have additional design considerations, in particular around whether to use words or images as stimuli. Although there is evidence that images activate meaning faster than words [Carr et al. 1982], it is more difficult to select an unambiguous image than an unambiguous word. Single words are thought to maximise the likelihood of activating related concepts, because they are easier to parse than phrases. However, subliminal word primes should avoid ironic effects. For example, Earp et al. found that "no smoking" is unsuitable as a prime because it activates concepts related to smoking [Earp et al. 2013]. Our Study 6.3 explores the question of stimulus type by comparing the impact of photos, text and polygons.

Prime Delivery

Subliminal priming is delivered by displaying the stimulus for a period of time that makes people unable to consciously recall the stimulus. Yet there is some debate about appropriate timings.

Previous studies have used durations ranging from 4ms [Murphy and Zajonc 1993], 5.55ms [DeVaul et al. 2003], 16.67ms (i.e. 1 frame at 60 frames per second, fps) [Dijksterhuis 2004; Hull et al. 2002; Strahan et al. 2002], 30ms [Veltkamp et al. 2011] and 33ms (2 frames at 60fps) [Aranyi et al. 2014].

Masking

Subliminal priming cannot be done on smartphones without users being aware that *something* is happening, for example seeing flickers related to stimuli exposure, since humans can detect flickers at rates over 500 Hz [Davis et al. 2015a]. Smartphones also cannot replicate the precise millisecond or sub-millisecond exposure times of tachistoscopes [Sperdin et al. 2013]. Smartphone interventions may be able to use *masking*: the use of additional images shown in the same location as a target within a brief time period in order to reduce the target's visibility [Enns and Di Lollo 2000]. Masking is a common technique in psychophysics to limit or remove the ability of participants to consciously recall a target, particularly when there are technical constraints on target exposure times [Bachmann and Francis 2013].

However, choosing an appropriate masking method, duration, and mask type is not trivial. Firstly, a mask may be presented both before and after a target (sandwich masking), just afterwards (backward masking) or just before (forward masking) [Enns and Di Lollo 2000; Wiens and Öhman 2007]. Secondly, mask durations are also varied across experiments, from 50ms [Spalding and Hardin 1999] to 200ms [Aranyi et al. 2014]. Thirdly, masks may be a pattern (e.g. random dots [Ham and Midden 2010]), a similar image (e.g. a neutral face mask shown after a stimulus of an emotive face [Liddell et al. 2005]), a bright-field energy mask [Seamon et al. 1984] or a composite of all stimuli [Aranyi et al. 2014].

Greenwald et al. showed that sandwich-masking targets shown for 50ms meant that some subjects could consciously recall them [Greenwald et al. 1996]. To maximise the chance of stimuli being invisible to *all* subjects, for our studies we selected a sandwich-masking technique with a stimulus duration of 17ms, or one frame at 60fps [Google 2016a]. This is consistent with fMRI studies that suggest a subliminal threshold of ~20ms [Meneguzzo et al. 2014] – i.e. above 20ms a stimulus is likely to be consciously recalled by at least some subjects.

Affective primes

Researchers have used smiling and angry faces as affective primes, with random polygons as "non-affective primes" [Winkielman et al. 1997]. Murphy & Zajonc found that subliminal priming of non-

affective items with smiling faces improved liking of those items compared with those primed with angry faces [Murphy and Zajonc 1993]. The results show evidence that emotions can be elicited outside of awareness. Winkielman et al. [Winkielman et al. 1997] suggest that affective priming is more effective with unfamiliar targets, compared with trying to change pre-existing affect for familiar ones.

Subliminal priming in mobile apps

Several commercial subliminal apps are available. However, some have features that make them unlikely to be able to deliver subliminal priming effectively. Megabit [Megabit 2015] presents primes for 300ms, which contradicts the evidence of a subliminal threshold at 20ms [Meneguzzo et al. 2014]. iSubliminal [2015] presents long phrases as stimuli, which are unlikely to be processed in subliminal display times.

User acceptance of subliminal priming techniques

A key question is whether users would accept subliminal priming techniques, even with informed consent. In a separate survey of users of activity trackers (n=26)[6], we asked: "Would you consider enabling subliminal prompts on your mobile device?". People generally had fairly negative attitudes towards priming: 13 said "Definitely not", 7 "neutral", 1 "Definitely" and 5 people provided no rating.

The participant that responded "Definitely" said, "*Curious how and if this could work?"*. Reasons for responding "Definitely not" included scepticism over effects ("*Don't think it's useful*"), a rejection of the idea of subliminal prompting ("[prompts should] *be obvious or not at all*"); and possible fear about the technique ("*subliminal prompts sounds like it could scar[e] people*"). Neutral respondents also expressed possible fear ("*it does make me aware of the fact that anyone could [p]ut any sort of subliminal message in my devices and I wouldn't like that*"), and wanted subliminal prompts that would comply with their conscious goals ("*the messages should comply with my other […] goals and not conflict with them*").

Experiments Overview

Our set of experiments proceeded as follows: first we carried out a week-long pilot in-the-wild to investigate how we might use subliminal techniques in behaviour change applications on

[6] Not reported fully in this thesis for reasons of brevity

smartphones (Experiment 6.1); next we conducted rigorous timing tests on a set of experiment smartphones to determine precisely how long stimuli are shown for (Experiment 6.2); and finally we carried out two semi-controlled experiment on these experiment devices: the first to determine the immediate impact of 3 different types of subliminal primes on subsequent liking judgements (Experiment 6.3), and the second to explore semantic subliminal priming using numbers (Experiment 6.4).

Experiment 6.1: 1 week in-the-wild nonconscious goal reminders

Motivation

This in-the-wild pilot measured the impact of one week of goal-related subliminal primes, shown at unlock time, on measures of direct and indirect goal activation. The domain was physical activity because it is important for general health [Rhodes et al. 2012]. We also wanted to pick up on one of the key domains of interest to users: surveys 4.2 and 5.2 found respondents were concerned about exercise and sedentary behaviour.

Method

This experiment's intervention involved showing participants goal-related primes on their own phones at unlock time. Participants were requested to use PIN unlock to try to maximise user attention on the screen at this point. We used both subliminal affective conditioning by associating a goal word with a smiley ":)" and subliminal mere exposure in the form of many repetitions of the goal word.

Design

This experiment used a pre-test/post-test control group design for explicit and implicit measures of goal activation. For the explicit measure, our dependent variable was a self-report goal commitment scale. Our independent variables were intervention group (control and intervention, between-subjects) and session (pre- and post- intervention, within-subjects). For the implicit measure, our dependent variable was reaction time to goal-related word stimuli. Our independent variables were intervention group (control and intervention, between-subjects), session (pre- and post-intervention, within-subjects) and word type (active, inactive and neutral, within-subjects).

Reactance was measured at post-test. Our dependent variable was a reactance scale score (outlined below); our independent variable was intervention group (control and intervention, between-subjects).

Hypotheses

We hypothesised that:

1. H1 there would be a statistically significant interaction between intervention group and session. We predict that, when compared to the control group, participants in the intervention group would show increases in both explicit and implicit measures of goal accessibility at post-test compared to pre-test measures. We also predicted that the intervention group at post-test would show increases in positive attitude towards being active, and decreases in positive attitude towards being inactive compared to the pre-test measures and control group.
2. H2 there would be no evidence of statistically significant differences in reactance scores between participants in the control vs intervention group.

Participants

38 participants (24 female, Mean age = 28.8 years, SD 8.22 years) took part. All were adult native English speakers who owned Android devices and used a PIN unlock, recruited at the University of Birmingham. 34 participants were included in the final analysis: 17 in a control group, 17 in an intervention group. 1 other participant in the intervention condition was excluded because they reported they saw the prime on unlock. 3 other participants were excluded because they did not use their phones during the week. This study has similar sample sizes to related work that has found effects [Aranyi et al. 2014; Dijksterhuis 2004; Strahan et al. 2002].

Recruitment material asked for people who wished to be more active, to address evidence that participants need to be motivated to pursue a goal for subliminal goal priming to be effective [Strahan et al. 2002]. All participants gave consent to participate in an experiment that “may prompt you to be more active”, but were naïve to the subliminal nature of the experiment until the end.

Prime Conditions

The experiment had a between-subjects intervention group condition: 1) an *intervention* group that received a goal prime at smartphone unlock time and 2) a *control* group that did not receive this

prime at unlock. Participants were randomly assigned, balanced for gender, to either the intervention group or the control group. For both conditions, all experiment materials (adverts, emails, surveys, instructions) repeatedly contained the prime *active :)*. Participants were also asked to form a specific active goal for the duration of the experiment. They were advised that the goal should be clear, specific and relatively difficult to achieve, in line with Goal Setting Theory (GST, [Locke and Latham 2006]).

PRIMING PROCEDURE

Participant unlocks **Blank (~500ms)** **Mask (~51ms)** **Stimulus** **Mask (~51ms)**

Figure 6.1. Unlock procedure – intervention

Participant unlocks **Blank (~500ms)** **Mask (~51ms)** **Mask (~51ms)**

Figure 6.2. Unlock procedure – control

After unlock, following a 500ms pause, a sandwich-masked stimulus was shown in black font on a white background in the centre of the screen for both conditions. *Intervention* participants (Figure 6.1), were shown the *active :)* stimulus for one frame (~17ms at 60fps [Google 2016b]), sandwich-masked by a non-word pre- and post- for 3 frames (~51ms at 60fps). The non-word was chosen to mask each character of the stimulus including the smiley characters. *Control* participants were only shown the non-word masks for ~102ms (Figure 6.2).

For the *Intervention* condition, we used a simple word, *active*, as a goal prime. This was chosen as it was relevant to the recruited participants' goal (i.e. to be more active) ensuring that it was goal-relevant [Strahan et al. 2002]. It is also commonly understood to form part of a general action goal [Albarracin et al. 2011]. We used text rather than a potentially faster-parsed image because of the difficulty of selecting an image that would be meaningful to a large group of people. The smiley was included to add affective conditioning for the goal prime [Custers and Aarts 2007]. We used a punctuation-based smiley :) because of evidence from neuroscience that these sorts of smileys are readily interpreted as smiling faces and provoke similar brain responses [Churches et al. 2014], and evidence that smiling faces can be effective subliminal affective conditioning cues [Ham and Midden 2010]. This smiley also has less ambiguity than a smiling-face photo or pictograph since pictographs differ across platforms and software versions [Tigwell and Flatla 2016], and selecting a photo means making choices about a person's characteristics such as gender that might make a difference in impact [Deutsch 1990].

Measures

To measure goal accessibility, we used an implicit measure and an explicit measure, both pre- and post-intervention. The implicit measure was reaction time in a modified Stroop task [Williams et al. 1996] . The explicit measure was a subscale of the Hollenbeck, Williams, and Klein (HWK) measure of goal commitment [1989] as validated by DeShon & Landis [1997].

IMPLICIT MEASURE

The modified Stroop task is an *implicit* measure because it uses reaction times (RT) to estimate processing bias towards different categories of words, rather than using self-report. Increases in RT in such tasks indicate higher activation for the longer-response words because they interfere more with the colour-naming task. Using this task builds on evidence that smartphones are a viable tool to deliver reaction-time based assessments [Enock et al. 2014]. Our modified Stroop followed Berry & Spence [2009] to measure RT in a colour naming task for three word types: *active, inactive and neutral* related words (forming the independent variable *Word Type* in the analysis below).

The neutral words used were matched for length and frequency with the active and inactive words using the British National Corpus [BNC 2016]; word stimuli are shown in Table 6:1. Our hypothesis was therefore that reaction time for intervention participants to active words would increase in comparison to the other word groups, representing higher interference from the repeatedly-activated 'active' concept.

Stroop category	*Word*
Active	active, walk, move, lively
Active control	writer, leaf, none, candle
Inactive	static, asleep, idle, lazy
Inactive control	inside, hammer, back, prop

Table 6:1 Stroop word stimuli

EXPLICIT MEASURES

To test hypothesis H1, that the intervention would have an impact on explicit measures of goal accessibility and attitude, we used the HWK sub-scale and a set of attitude semantic differentials. The HWK sub-scale is an explicit measure using Likert scale 1-5 ratings on goal commitment statements shown in Table 6:2. We added "I like this goal" as a proxy for positive affect. Goal importance and affect are argued to be strong predictors, along with goal progress, of feelings of success [Locke and Latham 1990].

HWK item
Quite frankly, I don't care if I achieve this goal or not. (R)
I am strongly committed to pursuing this goal.
It wouldn't take much to make me abandon this goal. (R)
I think this goal is a good goal to aim* for.
I am willing to put in a great deal of effort to achieve this goal.
I like this goal

**original wording = "shoot"*
(R) = reverse scored

Table 6:2 HWK Goal Commitment scale questions

Table 6:3 shows the 8 semantic differentials used to measure general attitude towards being active and inactive.

To what extent do you feel that being ACTIVE / INACTIVE is:	
Important	Unimportant
Harmful	Beneficial (R)
Healthy	Unhealthy
Foolish	Wise (R)
Enjoyable	Unenjoyable
Pleasant	Unpleasant
Satisfying	Unsatisfying
Interesting	Boring

(R) = reverse scored

Table 6:3 Attitude semantic differentials

We expanded on the set of semantic differentials used in study 5.1, adding “Foolish-Wise” and “Interesting-Boring” to derive a richer attitude score, and measured the items on a 5-point rather than on the 7 points as before to make the procedure simpler.

To test hypothesis H2, that there would be no evidence of differences in reactance between the intervention groups, we calculated a post-test reactance score from a set of 8 explicit attitude statements towards the app. Dillard & Shen show that reactance can be measured using anger and negative cognition components [2005]. Reactance items are shown in Table 6:4.

To what extent did you find the app:
Easy to use | Difficult to use
Easy to ignore | Difficult to ignore (R)
Made me angry | Did not make me angry (R)
Helpful | Unhelpful
Enjoyable | Not enjoyable
Annoying | Not annoying (R)
Irritating | Not irritating (R)
Aggravating | Not aggravating (R)
(R) = reverse scored

Table 6:4 Reactance scale items

Procedure

Participants were recruited via social media across the University of Birmingham. They received a link to a demographics survey to start the experiment, after which they were prompted to form and declare an active goal, and completed the HWK measure. They were randomly assigned to one of the two conditions, balanced for gender. Participants received a download link to an Android app. The first task in the app was to complete the modified Stroop task.

Figure 6.3. Modified Stroop task example

The modified Stroop task is shown in Figure 6.3. Following a short practice, participants were shown each word from the stimuli list at random in each of four colours, with a restriction that two words of

the same colour should not appear at adjacent times. Participants were asked to select the correct colour as quickly and accurately as possible. We recorded reaction time and correct selection.

The app then primed each group (intervention and control) for a week at unlock time as outlined above. At the end of the week of priming, participants were asked to complete a second modified Stroop task, and received a link to an online survey to measure Reactance and the HWK measure. Participants were asked whether they had seen any words on unlock, and which ones if any.

RESULTS

APP USAGE

Mean daily unlocks (and therefore stimulus exposures) was 49.0 (*SD* 28.0). A Chi-squared test of independence of unlock usage between intervention and control groups showed no evidence of a statistically significant difference $X^2(1, N=34) = .06$, $p = .80$.

To examine hypothesis H1, that our intervention would increase explicit and implicit goal activation measures, we examined the HWK goal commitment score (explicit measure); reaction times to 'active' words in our modified Stroop task (implicit measure); and our explicit measures of attitude towards activity and inactivity.

GOAL COMMITMENT

Table 6:5 shows descriptive statistics for the HWK measure, and Figure 6.4 shows a barplot with 1 SE error bars for the same data.

Group	*Session*	*N*	*Mean*	*SD*
Control	Pre	17	4.12	0.52
	Post	17	3.93	0.48
Intervention	Pre	17	4.42	0.34
	Post	17	3.97	0.63
Total	Pre	34	4.27	0.46
	Post	34	3.95	0.55

Table 6:5 HWK mean descriptive statistics by session and intervention group

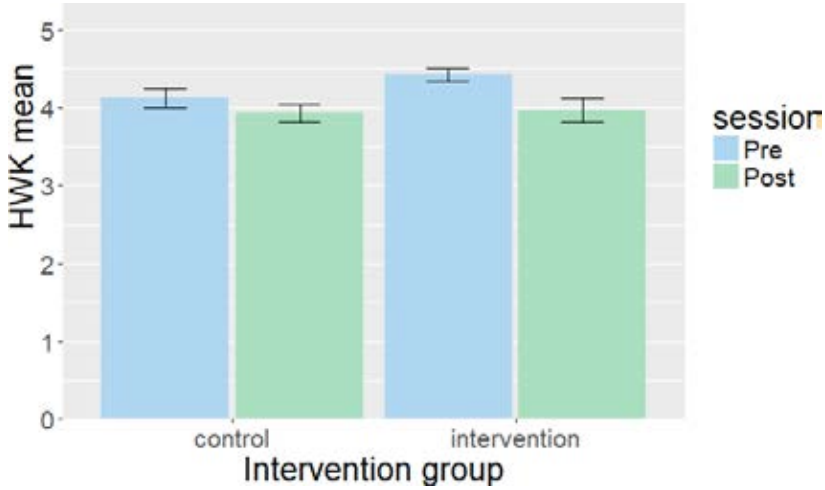


Figure 6.4 HWK mean barplot with 1SE error bars

HWK measures for each intervention group and session were tested for normality (all group x session cells Shapiro-Wilk p>.05 except control-pre W= 0.89, p=.05) and homogeneity of variance, which showed no evidence the variances differed significantly between groups $F(3,64)=1.71$, p=.17. We ran a 2x2 mixed-ANOVA to explore the effects of intervention group as a between-subjects factor (control or intervention) and session (pre or post) as a within-subjects factor on the HWK score. The model showed no statistically significant interaction effects between intervention group and session on the HWK measure ($F(1,32)=1.28$, p=.27), nor a statistically significant main effect of group ($F(1,32)=1.82$, p=.19), but showed a statistically significant main effect of session between pre- (mean=4.27) and post- (mean=3.95) sessions, $F(1,32)=7.43$, p =.01, η_p^2= .19. Thus there is no evidence to support our hypothesis that our intervention would improve scores (no statistically significant interaction effects), but there is evidence that goal commitment scores decline over time, regardless of intervention.

MODIFIED STROOP

One participant was removed because of a high error rate (27.5%) and another participant's second session data was lost, so the final sample included 32 participants (16 in each condition) with 8365 trials. 161 colour-naming errors (1.92%) and 10 outliers with reaction times more than 8,000 ms (0.12%) were removed in line with Dresler et al. [2009]. Table 6:6 shows the mean reaction times (in ms) for each intervention group (control or intervention), session (pre or post) and word type (active, inactive or neutral), with a barplot (1 SE error bars) for the same data shown in Figure 6.5.

		Word Type		
Group	*Session*	*Active*	*Inactive*	*Neutral*
Control	Pre	934 (±349)	903 (±290)	940 (±333)
	Post	897 (±279)	905 (±279)	918 (±318)
Intervention	Pre	1022 (±479)	1049(±505)	1041 (±500)
	Post	1005 (±476)	1037 (±532)	1013 (±496)

Table 6:6. Stroop colour-naming reaction times (ms) across word types, intervention groups and session

Our hypothesis was that if the intervention was successful, correct reaction times to active-related words would increase in the post-test session for participants in the intervention condition compared to the control condition and the pre-test session. This is because as exposure to the *active :)* prime activates their goal-related associations, active words become more salient and interfere more in the colour naming task. Reaction times to neutral words should not change, and inactive word reaction times may decrease as inactivity becomes less salient relative to activity.

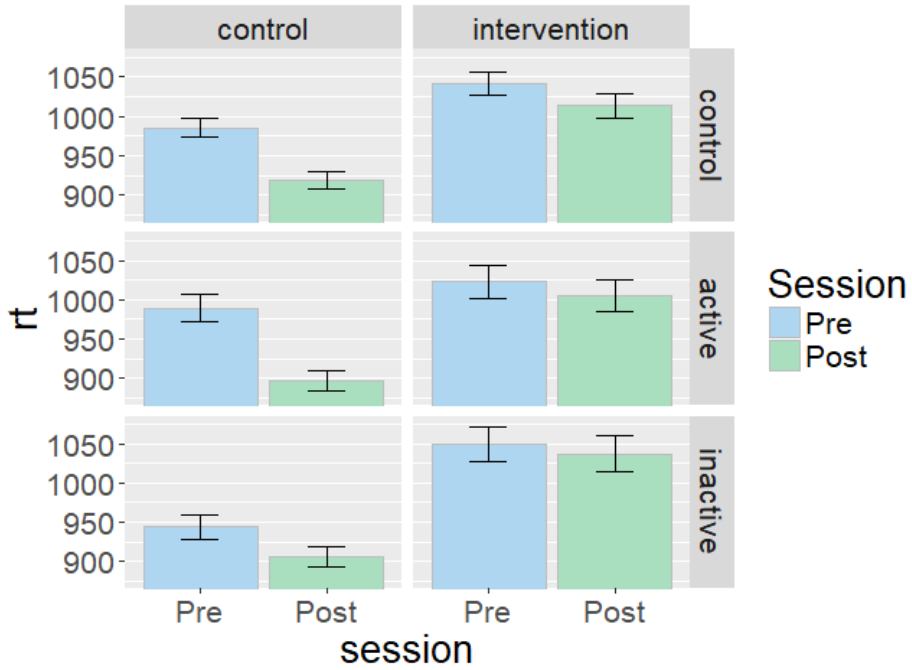


Figure 6.5 Stoop colour-naming reaction times (ms) across word types, intervention group and session (1 SE error bars)

We constructed a GLMER model to explore the effect of condition (control and intervention, control as baseline), session (pre and post, pre as baseline) and word type (neutral, active, inactive, neutral as baseline) on reaction time in the remaining 7944 trials. We trimmed 387 (4.87%) trials based on model residuals. The model that converged (R^2_{ps}= .33) included within-participant random slopes for session. The results in Table 6:7 show that the highest-order statistically significant interaction is Post:Intervention:Active (*b*=24.91, *SE*=12.00, *t*=2.07, *p*= .04). Note that the *p* values given are not Bonferroni-corrected. The Bonferroni corrected significance level for 11 comparisons at the 95% confidence level would be .0018 (=.05/11).

To ease interpretation, we also plotted the model's estimated marginal means generated by the lsmeans package [Lenth 2016], and their 95% confidence intervals in Figure 6.6. This shows that for the intervention group, correct responses to both control and active words are predicted to be faster in the post-test, while inactive words RT did not drop by as much. However, post-hoc Tukey-adjusted pairwise tests indicates no statistically significant difference between Intervention-Pre-Active and Intervention-Post-Active (*b*= 19.69, *SE*=20.85, *z*=0.94, *p* =.99). There is therefore no evidence to support our hypothesis that our intervention would slow reaction times to active-goal-relevant words only because they have become more accessible.

Fixed effects	*Estimate*	*Std. Error*	*t value*	*p value*
(Intercept)	939.93	14.90	63.09	<.001
Post	3.84	13.46	0.29	0.78
Intervention	126.70	19.56	6.48	<.001
Active words	-8.03	7.45	-1.08	.28
Inactive words	-22.92	8.64	-2.65	.01
Post:Intervention	-35.54	19.77	-1.80	.07
Post:Active words	-12.91	8.97	-1.44	.15
Post:Inactive words	10.72	10.67	1.00	.31
Intervention: Active words	-7.15	10.40	-0.69	.49
Intervention:Inactive words	21.93	13.03	1.68	.09
Post:Intervention:Active words	24.91	12.00	2.07	.04
Post:Intervention:Inactive words	11.07	15.00	0.74	.46
Random effects	*SD*			
Participant (Intercept)	60.76			
Session (Session Post)	44.66			
Residual	0.01			

*Model formula: RT ~ (session * condition * word type) + (1 + session | participant)*

Table 6:7 Modified Stroop LMER results

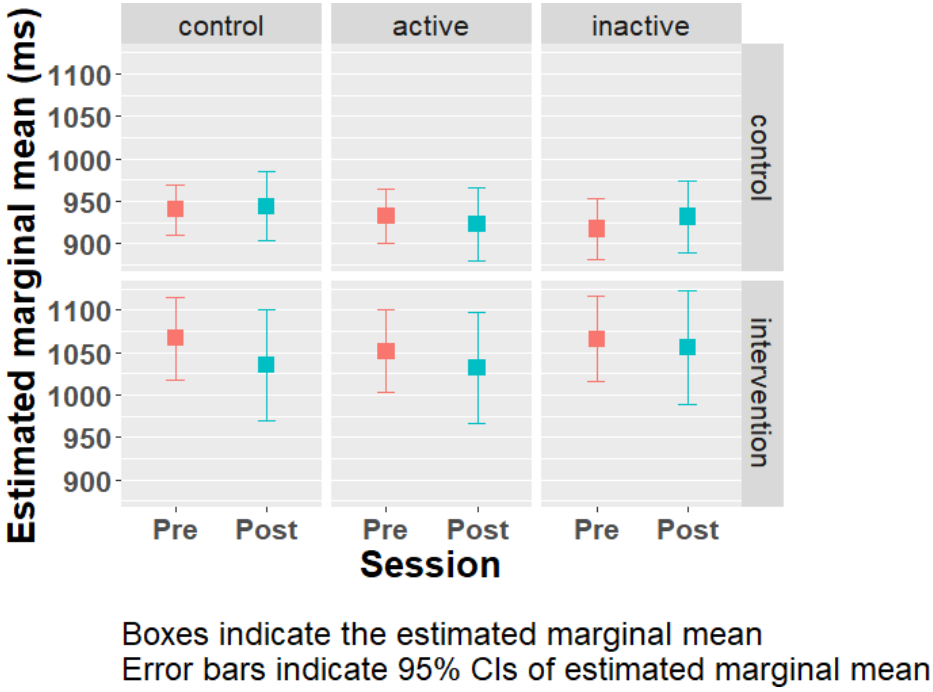


Figure 6.6 Estimated marginal means and 95%CIs for Stroop model RTs (ms)

ATTITUDES TOWARDS ACTIVITY AND INACTIVITY

Descriptive statistics are for our attitude scores towards being active and inactive are shown in Table 6:8 and Figure 6.7.

		Active		*Inactive*	
Condition	*Session*	*Mean*	*SD*	*Mean*	*SD*
Control	Pre	4.32	0.43	1.86	0.59
	Post	4.38	0.35	1.89	0.68
Intervention	Pre	4.20	0.34	1.89	0.65
	Post	4.29	0.70	1.68	0.77

Table 6:8 Attitude semantic differential scale descriptive statistics

To examine our hypothesis H1 that the intervention would improve positive attitudes towards being active and reduce positive attitude towards being inactive, we examined the two attitude score dependent variables (active and inactive) across our two independent variables: intervention group (control and intervention, between-subjects) and session (pre- and post- intervention, within-subjects).

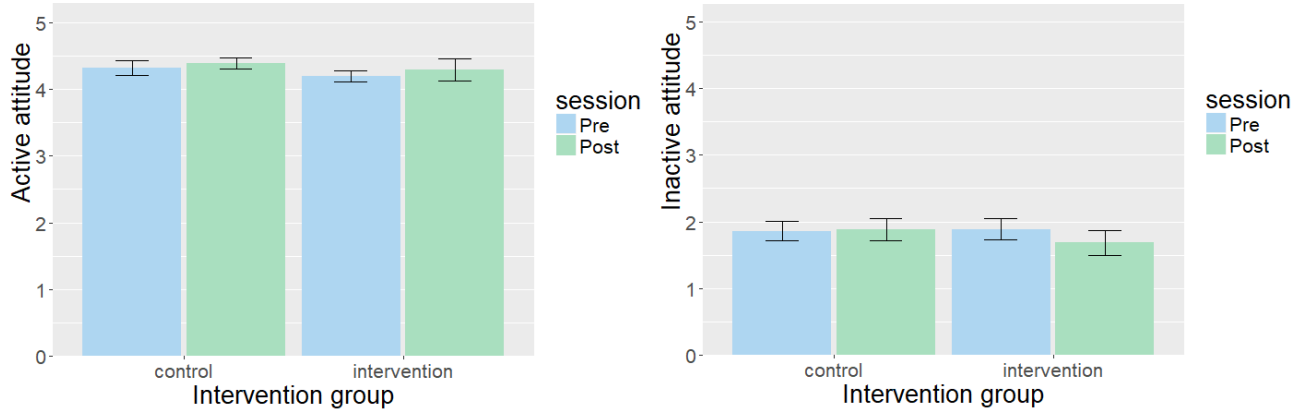


Figure 6.7 Barplots with 1 SE error bars for (left) attitudes towards activity and (right) attitudes towards inactivity

We first examined the active attitude dependent variable. A Shapiro-Wilk normality test indicated that positive attitude data was not normally distributed for the post-session control (W=0.88, p=.03) and intervention groups (W=0.86, p=.01), both pre-session normality tests p>.05. There was no evidence of a violation of homogeneity of variance (F(3,64)=1.62, p=.19). Wilcoxon rank-sum tests showed no evidence of an impact of session on positive attitude for either intervention (W = 107, p=.20) or control group (W=135, p=.75).

Mean inactive attitude was assessed between the intervention groups across sessions for normality, which showed no evidence of departures from normality (all group x session tests p > .05) and

homogeneity of variance, which showed no evidence of differences in variance ($F(3,64)=0.21$, $p = .89$). A 2x2 mixed-ANOVA showed no evidence of statistically significant differences for main effects (group $F(1,32)=0.26$, $p=.61$; session $F(1,32)=0.33$, $p=.57$) or interaction between group and session $F(1,32)=0.59$, $p=.45$. Therefore there was no evidence to support the hypothesis that explicit attitudes would change as a result of the intervention.

REACTANCE

We generated a reactance score by averaging over reported anger and negative feelings towards the app from the post-test data gathering session. Mean reactance for the intervention group was 0.34 (SD=0.75) and for the control group was 0.56 (SD = 0.67). To examine hypothesis H2 that the intervention would not cause reactance, we examined the effect of our between-subjects intervention group independent variable (intervention or control) on our dependent variable, mean reactance score. The data in each group showed no evidence of departures from normality (Shapiro-Wilk intervention $W=0.93$, $p=.25$; control $W= 0.89$, $p=.06$) and no evidence of heterogeneity of variance ($F(1,32)=0.01$, $p=.93$). A Welch Two Sample t-test showed no evidence of a difference in reactance scores between the control and intervention groups, $t(31.63) = 0.90$, $p = .37$, mean difference = 0.22, 95%CI[-0.28, 0.72], Cohen's $d=0.31$.

STIMULUS RECALL

26 participants (76%) responded "yes" to the question "Did you notice any words appear on the screen after unlocking your phone?", but no participants could correctly identify the words. Some who responded "yes" reported confusion: *"Was it meant to do something? It just had a v.quick flash when I unlocked my phone".*

DISCUSSION

Contrary to our first hypothesis that our intervention would improve explicit measures of goal accessibility, the goal commitment HWK score decreased over 1 week, regardless of subliminal primes. This alone is not necessarily problematic, since other research has found evidence for effects of priming outside conscious goal commitment [Hassin et al. 2009]. However, the modified Stroop tests showed no evidence that the intervention had an impact on nonconscious goal activation, contrary to our hypothesis that our intervention would improve goal accessibility, which should slow reaction times to naming active-goal-relevant words compared to other word types and the control group.

Participants unlocked their phones on average 49 times a day, a higher number than some previous research of 25 mean unlocks per day [Hintze et al. 2014], although Truong et al. found highly variable numbers of daily unlocks of between 5-105 [Truong et al. 2014], in line with our SD of unlocks of 28.0. Most participants reported seeing words that they could not identify on unlock, reinforcing our design decision to select unlock time as the time most likely to hold user attention.

Limitations

This experiment was limited by a small number of participants running the app for only a short amount of time. The data was noisy: our Stroop data shows the intervention groups had broadly different response times to active words at the start of the experiment, and the GLMER R^2_{PS} of .37 indicates a relatively low correlation between fitted and observed values. Since the study was run in-the-wild, although we targeted unlock as an intervention time at which participants were likely to be paying attention to their phone, we had no direct eye gaze metrics for this, nor for the Stroop test participation.

Note from Figure 6.7 that the experiment may not have had sufficient power for our measure of attitude towards activity would detect a small improvement in attitude. Participants recorded a mean response of 4.26 on this 5-point scale at the outset, leaving little room to detect improvement in the context of confidence intervals approximately twice those of the 1 standard error bars shown. From Figure 6.6, showing 95%CIs for Stroop task reaction times, the experiment would only have been able to detect differences in the intervention group of approximately 100 ms, with average marginal means of 1050ms for the intervention group and 925ms for the control group, although note that estimated marginal mean CIs can be misleading because they do not include random effects. Although we expect longer RTs in-the-wild compared to lab experiments, we note that a lab-based experiment measuring responses to exercise and sedentary words [Berry 2006] showed means of around 588ms for exercisers and 636 for non-exercisers (although *n* for the latter group was small, n=8, and the experiment found that these differences were not significant).

Further work is required to validate the use of emotional Stroop tests on smartphones in the wild. Future studies could also gather additional information about the performance of the app in displaying the prime, i.e. by logging frame display times. Therefore it is difficult to determine why we found no evidence for an impact of our intervention.

We conducted further investigations into subliminal priming with a series of follow-up studies to help disambiguate these issues. Experiment 6.2 addresses possible technical issues with delivering image-

based primes on smartphones by measuring precise frame times for primes on particular experiment phones. Experiment 6.3 uses these phones to implement immediate reaction tests, in semi-controlled conditions where users were asked to concentrate, with direct measures of visibility and likeability. We also expanded the number of participants to deal with a possible lack of power in experiment 6.1.

Study 6.2: Technical Feasibility

Our motivation was to examine in more detail the technical boundaries in displaying primes to help disambiguate the lack of results in experiment 6.1. We therefore explored the timing parameters of displaying sandwich-masked subliminal primes on specific smartphones. The tests were constrained to a set of four same-batch Android smartphones, later also used in experiments 6.3 and 6.4.

Method

APPARATUS

We ran the experiment timings app on a set of four Samsung Galaxy Nexus smartphones running Android 4.3. Android smartphones are capped at 60 fps or ~16.67ms per frame and use vertical sync to align the software's refresh rate with the display hardware refresh rate [Google 2016b].

PROCEDURE

We built an Android app to test frame durations for showing short-lived stimuli. We used the sandwich-masked stimulus exposure (mask-stimulus-mask) shown in Figure 6.9 using 3 different types of stimuli (text, polygons and photos, see Figure 6.11). We ran multiple sessions on each of 4 experiment phones. Mask duration was set at 3 frames (50ms at 60fps), while the stimulus duration was set at 1 frame (~16.6ms at 60fps). No images were preloaded. We used Android's Choreographer functionality [Google 2016c] to log precise frame times for stimulus animation. Where frame time exceeded 25ms, the mid-point between frames at 60fps, we recorded a "dropped frame".

Although it is possible to measure exact frame durations, this is not the same as a length of the stimulus actually appearing because each pixel takes time to update once it receives the signal: the pixel transition rate. LCD television screens pixel response rates show rates of approximately 1 frame duration or longer [Elze and Tanner 2012], but we were unable to locate any stated pixel response times for manufacturers of LCD or AMOLED smartphone displays for comparison. To investigate

further, we filmed our experiment on our Samsung Galaxy Nexus' AMOLED display using a GoPro Hero 4in WGVA in 240fps mode, equal to 4.17ms per frame.

RESULTS

FRAME TIMINGS

Results are shown in the first row of Table 6:9. There were some dropped frames, 0.09% of total (n= 89714), and all of these occurred during the first or second frame captured. This suggests that the animation object may sometimes not be ready by the first VSYNC, but that subsequent frames appear at around 60fps. As a comparison, we also ran the timing app with Wi-Fi connected as a proxy for extra load. The results are in the second row of Table 6:9.

Wi-Fi state	*Dropped frames*	*Length of non-dropped frames in ms*				
		Median	*Max*	*Min*	*Mean*	*SD*
Off	0.09%	16.97	17.97	15.99	16.98	0.17
On	0.32%	16.97	18.64	15.25	16.97	0.19

Table 6:9. Frame timings

A Kruskal-Wallis test showed no statistically significant differences between frame lengths between our devices with Wi-Fi off [$X^2(3) = 1.42$, p=.70], but a statistically significant difference with Wi-Fi on [$X^2(3) = 18.38$, $p < .001$]. A higher number of dropped frames occurred with Wi-Fi on (0.32%) in multiple positions, not just the first frame.

PIXEL TRANSITION RATES

Figure 6.8 shows transitions between mask and stimulus from a GoPro recording (4.17ms per frame).

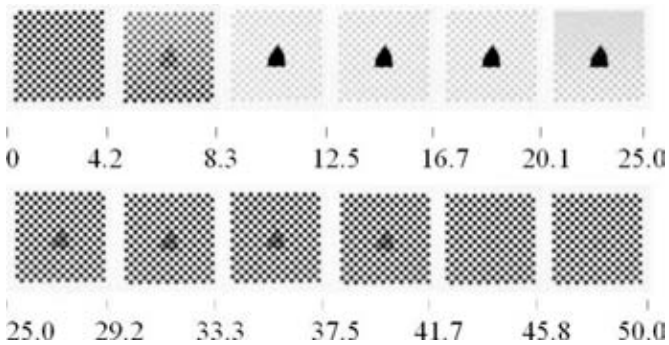


Figure 6.8. Mask-polygon stimulus-mask screenshot timeline in ms

The stimulus is clearly discernible for 4 frames, ~16.7 ms (8.3ms—25ms), although transitions between the stimulus and mask before and after the stimulus is fully visible can be seen.

The study app was filmed on the experiment phones under the same conditions as Experiment 6.3 (WiFi off, no other apps running) several times (n=10) on different occasions, with similar results.

Discussion

Overall, we have demonstrated that it is technically possible to show stimuli on Android smartphones at times comparable to those used in subliminal priming studies in psychology labs. The timings show that a 1-frame item appears for ~16.7 ms and a 3-frame mask appears for ~51ms on the experiment phones when Wi-Fi is disabled. We also found that enabling Wi-Fi leads to unpredictable dropped frame rates and hence unpredictable display times, a finding relevant for comparative studies. A future task is to confirm whether these results generalise to different types of display hardware.

We have therefore shown that subliminal priming is technically possible on our Android smartphones. However, with respect to RQ2, we still have not established how best to deliver subliminal priming on smartphones such that it has a measurable impact. The lack of statistically significant results in Experiment 6.1 may have been due to variations in user technology, the incidental nature of the priming delivery, i.e. at unlock, which meant priming exposures varied between participants and potential decay effects, lack of relevance of the primed word and/or low power. To disambiguate these points, we next limited our priming experiments to these experiment phones, with an experiment design measuring the immediate impact of a range of stimuli more closely based on those shown to have effects in psychology labs, with a larger number of people.

Experiment 6.3: Stimuli Priming

Motivation

The previous study showed that it is technically possible to display items subliminally on our experiment Android smartphones. However, it is not yet clear whether the statistically non-significant results from Experiment 6.1 were due to the procedure having little or no impact when delivered on smartphones. Therefore we next concentrated on determining whether we can demonstrate an immediate impact of subliminal priming on smartphones, and whether there are differences between different stimulus types.

This study built on subliminal priming experiments from psychology [Bornstein et al. 1987; Seamon et al. 1984; Kunst-Wilson and Zajonc 1980]. To demonstrate subliminal priming, experiments need to satisfy two conditions: participants cannot consciously recall the stimulus (direct effect); and the

same stimulus has some measurable indirect effect [Dijksterhuis et al. 2005; Draine and Greenwald 1998]. A common measure of the indirect effect is participant preference of the primed stimulus [Monahan et al. 2000].

We selected three different types of stimuli: polygons, photos and text as shown in Figure 6.9. The stimuli were non-affective (non-smiling faces, abstract polygons and text) to focus the study on exploring the effects of subliminal mere exposure effects. We selected polygons because they have been used in previous subliminal priming experiments and could therefore act as a baseline comparison for text and photos. We selected text because we used it in Study 6.1 and photos because images can activate meaning faster than words [Carr et al. 1982].

This study was conducted in semi-controlled conditions: we approached people in-the-wild, but participants used the experiment phones and were asked to concentrate for the duration of the session, thus reducing potential distraction issues from our in-the-wild Experiment 6.1.

METHOD

DESIGN

There were 2 independent variables in the experiment:

1. Repetitions Group– how many times the prime was shown to participants [3 levels: 0xRepetitions (Control, N=29), 1xRepetitions (N=32) and 3xRepetitions (N=40)]
2. Stimulus Type – the type of stimuli shown to participants [3 levels: polygon, photo and text].

Repetitions Group was varied between subjects with Stimulus Type varied within subjects. For Repetitions Group conditions, participants were unaware of which condition they were allocated to until they were debriefed at the end of the experiment. Experimenters were also unaware of the precise allocation of participants.

Our two binomial dependent measures were whether participants could correctly identify which stimulus they'd just been shown from a choice of two; and whether participants selected the primed stimulus when asked which they preferred from the same choice of two.

HYPOTHESES

Subliminal perception is argued to exist where there is no evidence that participants are able to correctly select the target item (i.e. the item they were primed with) yet participants prefer that

same item [Bornstein et al. 1987; Dehaene et al. 2006]. This means there should be no evidence of different rates of visiblity for those shown stimuli compared to the control, but evidence of different rates of preference compared to the control.

Our related hypotheses to examine subliminal priming were:

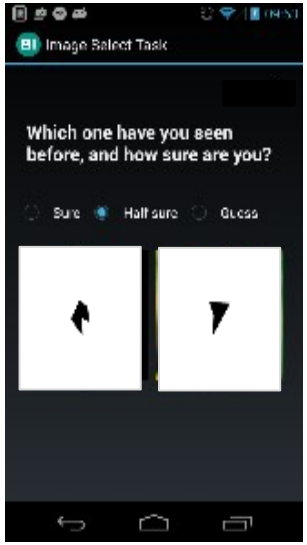
- H1: there would be no statistically significant simple main effect of Repetitions Group on the probability of participants being able to correctly identify the prime in the Visibility Task (the *direct effect*) or interaction with Stimulus Type. That is, there would be no difference in identification rates between the repetitions groups or evidence of a difference between Repetitions Groups that differed according to Stimulus Type .
- H2: where participants failed the Visibility Task, there would be a statistically significant simple main effect of Repetitions Group on the probability of participants preferring the prime regardless of stimulus type (the *indirect effect*). We predicted that, compared to the control 0xRepetitions group, participants in the other Repetitions Groups would show increased preference rates for stimuli they had just been shown, regardless of Stimulus Type.

Participants

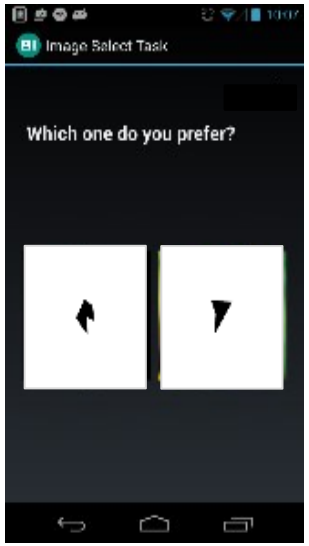
101 participants (36 women, age mean= 25.9 years, SD= 8.22 years, 1 participant declined to give their age) completed the experiment. Participants were recruited in person and via posters at our institution and in social and work situations within our social networks. They were offered a small non-monetary reward at the end of the experiment and could choose to enter a prize draw for a £30 voucher.

Task

The experimental task involved participants completing a series of trials, during which participants were shown a single masked *prime* stimulus (Exposure Phase). The priming procedure is shown in Figure 6.9.



Visibility task



Preference task

Figure 6.10. Selection Phase example (polygons)

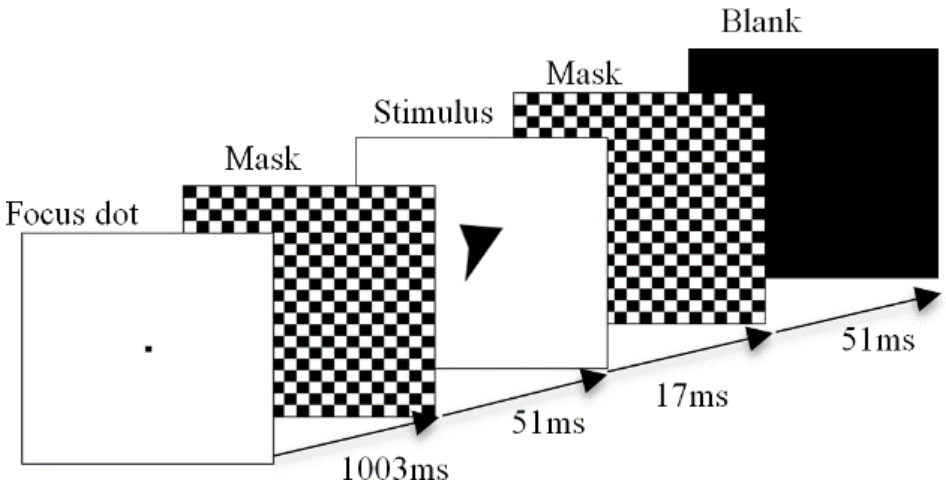


Figure 6.9. Exposure Phase (1x condition trial)

Group	*Example*	*Mask*
Polygon		
Photo		
Text	search	xxxxxxx

Figure 6.11. Stimuli groups, examples and masks

Participants were exposed to the primes as follows:

1. A focus dot for ~1003ms
2. A mask for ~51ms
3. A stimulus for ~17ms (prime)
4. A mask for ~51ms
5. A blank screen for ~204ms

The prime exposure procedure varied depending on the participants' Repetitions Group condition:

- 0xRepetitions (control) condition: steps 1-5 where the stimulus in step 3 was a blank image (n=29).
- 1xRepetitions condition: steps 1-5 repeated once (n=32).
- 3xRepetitions condition: step 1-5 repeated three times (n=40).

After priming, participants were immediately given two 2-alternative forced choice tasks in sequence to measure (i) whether they had seen the prime (Visibility Task) and (ii) whether they preferred the stimulus they had been primed with (Preference Task). After answering both questions, participants switched back to the exposure phase to start another trial until they had been shown all the primes in each stimulus type group. The order of type groups and order of pairs within the type group were randomised between participants. The order in which items were shown as primes were also randomised within participants and between stimulus types.

Priming items

Over the task participants were primed with three Stimulus Types:

- Polygons (control stimuli): Black irregular polygons on a white background, 12.5px high, adapted from [Cornell 2016]; chequerboard mask
- Photos: 200x200px black and white headshots of people with neutral expressions from the Chicago Face Database [Ma et al. 2015], each pair balanced for the database's attractiveness rating, race and gender, and masked with a chequerboard mask.
- Text: a set of words shown in 42px Verdana bold black font on a white background. Words were menu items from the top 10 apps in the Android Play store, balanced for word length. The word pairs are given in Table 6:10. Each word was masked with a series of 'x's.

help-move	shop-open
reply-quit	attach-delete
report-recent	settings-sign up
new-add	log in-log out
refresh-search	print-pause

Table 6:10 Stimulus word pairs

In total, participants were exposed to 10 different polygons, 10 different words and 20 different faces, in line with [Kunst-Wilson and Zajonc 1980] for polygons & words and [Murphy and Zajonc 1993] for photos, thus making 40 trials for each participant. We used an ethnically diverse range of male & female faces (10 male, 10 female). Polygons were used as the baseline stimulus type because they have been shown to elicit subliminal mere exposure effects in previous experiments [Kunst-Wilson and Zajonc 1980]. We used photos and text as comparison stimuli because they are likely candidates for inclusion in behaviour change apps, and to re-examine text stimuli as a follow up to experiment 6.1. We used the same sandwich-masking technique and mask duration as in experiment 6.1. Example images from each group and corresponding masks are shown in Figure 6.11.

Measures

After the prime *Exposure Phase*, participants were shown two sets of two images, in sequence, and asked to select one of the images displayed in each case (Selection Phase). These sets were made up of a *target* stimulus identical to the prime[7], and a *distractor*, a randomly chosen stimulus that was different to the prime, but of the same stimulus type. Participants were asked:

1. Which one have you seen before? (*Visibility Task)*
2. Which one do you prefer? (*Preference Task)*.

The order of asking was randomised between participants. Whether participants selected the same image as the prime (i.e. the *target*, coded as a 1) or the *distractor* (coded as a 0) were recorded. Participant's selections in the Visibility Task form the binary outcome variable in the Visibility analysis and their selections in the Preference Task form the binary outcome measure in the Preference analysis, both reported below.

[7] In the Control condition, where participants did not experience a prime, one of the stimuli displayed was randomly assigned the role of the target.

Procedure

Participants completed the study on our experiment smartphones from Study 2: “clean” same-batch Samsung Galaxy Nexus smartphones running Android 4.3 with Wi-Fi disabled. They completed the task in natural surroundings such as the coffee room and our atrium. Prior to the test, participants completed a consent form, demographics and a training session. Participants gave informed consent based on an experiment that would “show images one by one for a very short space of time” but were naïve to the subliminal nature of the experiment until the end. All participants completed a brief training session before the experiment started. The training stimuli were colour flower photos.

During the main experiment, for each trial, participants were shown a target in the Exposure Phase, followed by a two-alternative forced choice between the target and its distractor stimulus in the Selection Phase as outlined above. Once the experiment was completed, participants were debriefed and thanked. A summary of the experiment procedure for a given participant is given in Table 6:11.

- User randomly assigned to Repetitions Group (0xRepetitions, 1xRepetitions or 3xRepetitions)
- User randomly assigned to always asked Visibility Task or Preference Task first
- User shown training phase
- Stimulus group order randomised (polygons; text; photos)
- For each stimulus group:
- Randomly assign whether first or second stimulus in group pairs list (A1-B1, A2-B2, A3-B3, …, A*N*-B*N*) acts as the target (i.e. target stimuli always A or B; distractor stimuli are the other set)
- Group pairs list order randomised
- For each target-match pair:
- For each target-distractor pair in Stimulus Type list:
- Repetitions Phase: show target as prime based on user group assigned in Step 1 (0, 1 or 3 times)
- Selection Phase:
    - show target and distractor
    - ask user Visibility Task and Preference task in order selected in Step 2

Table 6:11 Pseudocode for experimental procedure

Results

Data analysis

Data with reaction times less than 200ms (n=246, 3.04%) was removed. The GLMER for the Visibility Task analysis had data from 101 participants with 4032 observations. The Preference Task analysis

was on a subset of data where participants answered the Visibility Task incorrectly, so that we could ensure the participants were not consciously aware of the stimulus, with 722 observations on 53 participants.

The dependent outcome variable in both the visibility and preference tasks—whether the stimulus selected was the *target* (1) or not (0)—is binary. Our GLMER models examined the effect of our independent variables Repetition Group (control, 1xRepetitions, 3xRepetitions) and Stimulus Type (photo, polygon and text) on the log odds of participants correctly selecting the target item (correct or not). Our baselines were control (no prime shown) and polygon, the latter chosen because of its affect-neutral appearance, which may not be the case with photos or text. The models included random intercepts for participant and target item to allow for random variation in responses both by individual participants and by individual items.

Visibility Task

In the Visibility Task, participants were asked to select the image they thought they had seen before. Figure 6.12 shows the results of the Visibility Task in terms of total proportions selected in each Repetitions Group condition by Stimulus Type. Note that the figure does not represent individual variability, which is accounted for in our model.

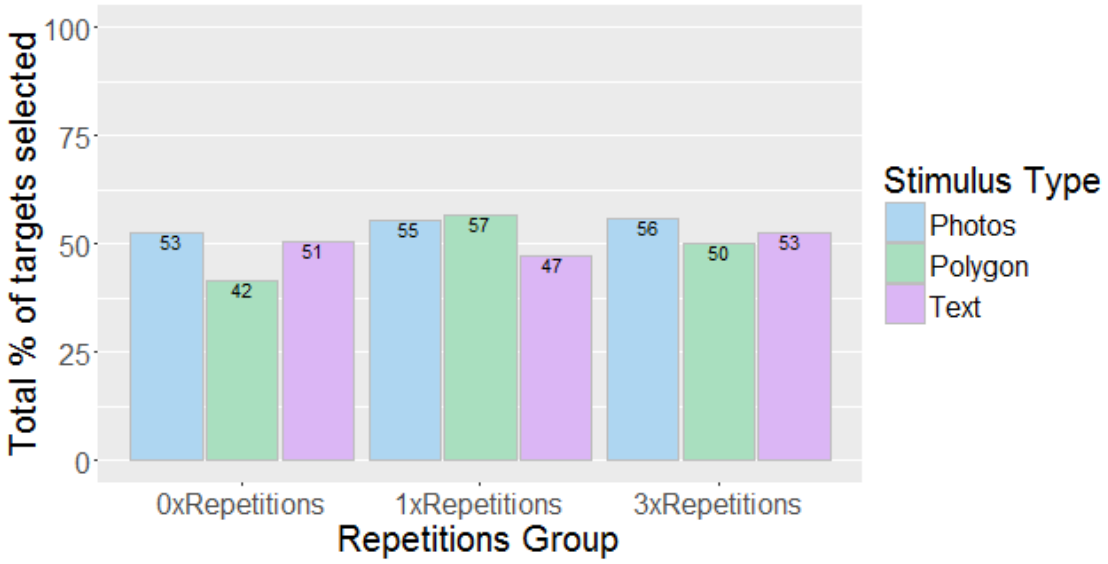


Figure 6.12 Total Proportion of Target Selections in Visibility Task by Repetitions Group and Stimulus Type

Table 6:12 summarises our Visibility Task model results (R^2_M=.05, R^2_C=.11). There was a statistically significant effect of *repetitions*, and no statistically significant interaction effects. Participants in the

1xR*epetitions* and 3xR*epetitions* conditions, regardless of stimulus type, were more likely to correctly select the target than baseline participants who were not shown a prime (*0xRepetitions*).

This does not support our hypothesis H1 that there would be no significant differences in detection rates between participant groups. In short, participants could see the stimuli to a certain extent. There was also a statistically significant simple effect of showing photos (b=0.41, SE=0.19, z=2.20, p=.03) on the likelihood of a participant correctly selecting the target compared to the polygon baseline condition.

This can also be seen from the Visibility Task results shown in Figure 6.12. Note that the *p* values are not Bonferroni-corrected, which would not affect the simple main effects of 1x and 3x Reps (critical *p* value = .0056) but does affect the statistical significance of the Photos condition.

Fixed effects	*Estimate*	*Std. Error*	*Wald Z*	*p value*
(Intercept)	-0.31	0.16	-1.93	.05
1xRepetitions	0.68	0.18	3.72	<.001
3xRepetitions	0.66	0.17	3.79	<.001
Text	0.21	0.21	0.98	.33
Photos	0.41	0.19	2.20	.03
1xText	-0.44	0.24	-1.8	.07
3xText	-0.22	0.23	-0.97	.33
1xPhotos	0.09	0.21	0.44	.66
3xPhotos	0.28	0.20	1.38	.16
Random effects	*SD*			
Participant (Intercept)	0.26			
Item (Intercept)	0.40			

*Model formula: correct ~ repetitions * type + (1 | user) + (1 | item)*

Table 6:12. Visibility Task analysis, summary effects

The plot of estimated marginal mean probabilities with 95%CIs is shown in Figure 6.13, which shows that the model predicts that detection rates for 1xPhotos, 3xPhotos, 1xPolygon and 3xPolygon will exceed the relevant control (0x repetitions) with no overlapping CIs.

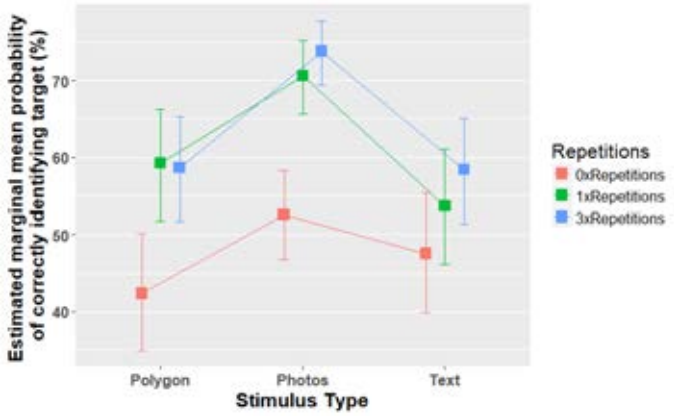


Figure 6.13 EMM probabilities of correct selection in Visibility Task with 95%Cis

Preference Task

To test the hypothesis that participants in 1x and 3x repetitions groups preferred items at greater levels than control group participants (0xRepetitions), we analysed the outcomes of the Preference Task ("Which one do you prefer?") where participants got the Visibility Task wrong, i.e. they did not correctly identify the image they'd see before. The Preference Task results in terms of total proportion of primed targets selected by Repetitions Group and Stimulus Type are shown in Figure 6.14. These results represent the proportions of answers that were switched between the tasks: i.e. participants changing their response to the 2-alternative forced-choice question between tasks (Visiblity Task incorrect, Preference Task correct). For example, in the 1x Photos condition, only 26% of correct targets were selected when the visiblity task was incorrect, representing a switch of 26%. The results therefore show a low degree of switching across the conditions (all < 50%).

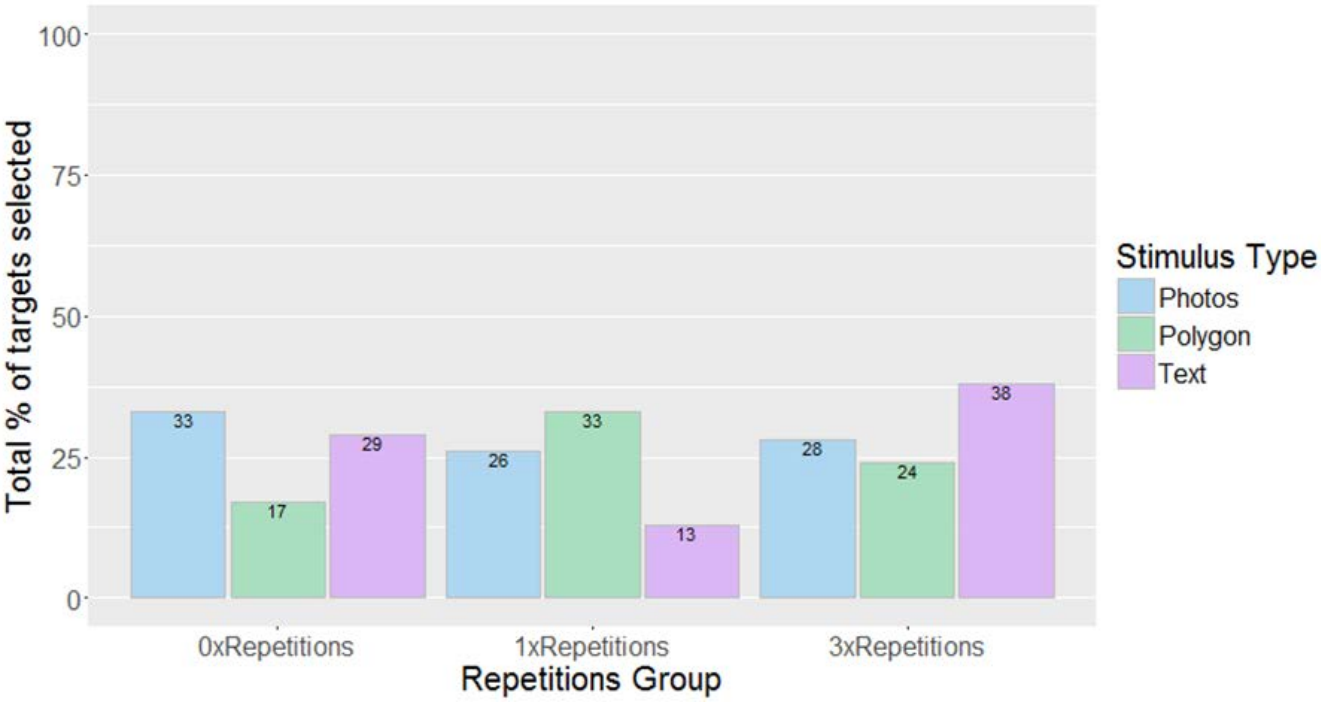


Figure 6.14 Total Proportion of Target Selections in Preference Task where Visibility Task was incorrect

Table 6:13 summarises the outcome of our Preference Task GLMER model (R^2_M=.05, R^2_C=.29). Note that the *p* values are not Bonferroni-corrected, although in this instance it would not make a difference to the statistical significance of the 1xText fixed effect (*p*<.001, Bonferroni-corrected critical *p* =.006).

Fixed effects	*Estimate*	*Standard Error*	*Wald Z*	*p value*
(Intercept)	-1.80	0.47	-3.81	<.001
1xRepetitions	0.91	0.61	1.50	.13
3xRepetitions	0.48	0.59	0.81	.42
Text	0.81	0.48	1.68	.09
Photos	0.83	0.44	1.89	.06
1xText	-2.20	0.67	-3.30	<.001
3xText	-0.09	0.61	-0.14	.89
1xPhotos	-1.20	0.60	-2.00	.05
3xPhotos	-0.58	0.58	-1.01	.31
Random effects				*SD*
Participant (Intercept)				1.00
Item (Intercept)				0.29

*Model formula: correct ~ repetitions * type + (1 | participant) + (1 | item)*

Table 6:13. Preference Task where Visibility Task was failed

The results show that the effect of repetitions is not statistically significant, i.e. there is no evidence that showing a stimulus to a participant increases the likelihood that they will prefer it when they

cannot see it (1xRepetitions p=.13; 3xRepetitions p=.42). The model also shows different effects across Stimulus Type: when participants cannot detect a Text stimulus, showing it once (1xText) decreases the likelihood of it being preferred (i.e. the participant switches their answer between Visibility and Preference tasks) compared to the baseline control condition (0xPolygon), (b=2.20, SE=0.67, z=3.30, p<.001), whereas there is no evidence that showing text three times makes an impact (p=.89).

This can also be seen in Figure 6.13 and from the plot of estimated marginal mean probability of people correctly selecting the target in the Preference Task after failing to identify the target in the Visibility Task shown in Figure 6.15. The figure shows that the data is noisy, with switching rates low overall (the vast majority below 50%), and particularly low for 1xText, i.e. participants in the 1xText condition are predicted to be consistent with their answers between Visibility and Preference responses compared to 3xText and 1xPolygon.

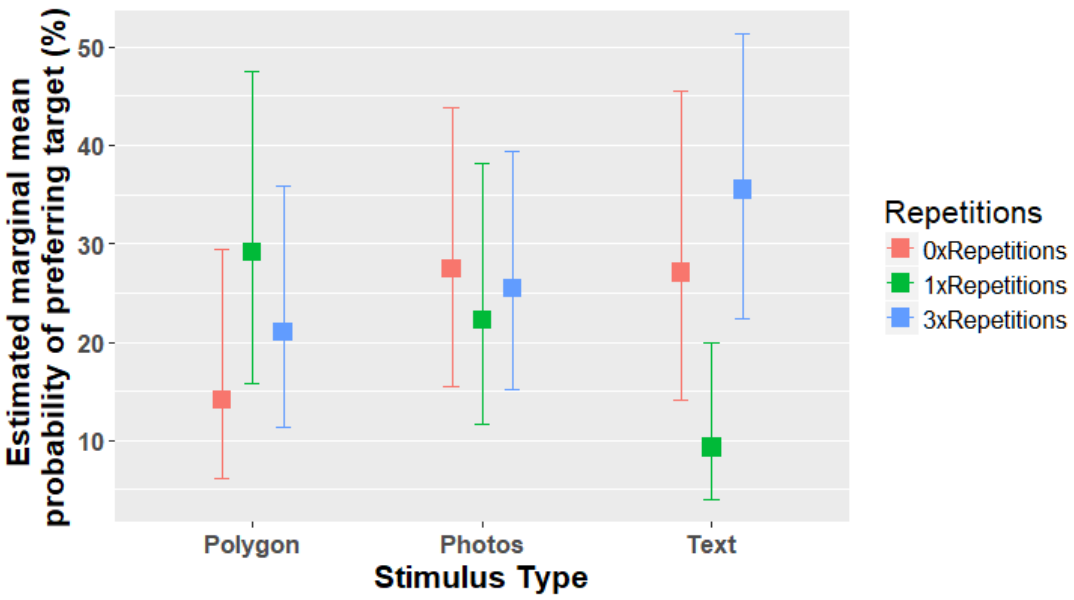


Figure 6.15 Estimated marginal mean probability of preferring target after getting the visiblity task wrong

Discussion

Our results indicate that subliminal priming effects on smartphones may be inconsistent, with contradictory results across different stimulus types. Using text seems detrimental to subliminal priming when primed once compared to the other conditions (a statistically significant negative impact for 1xText in Table 6:13).

There is some evidence that stimuli are difficult to conceal. Our participants could detect target stimuli to a certain extent when they were shown the prime once and three times, compared to the control, on our experiment phones. However, the marginal R^2 measure for the Visibility Model (R^2_M=.05) indicates that this detection effect seems to be small.

One explanation for detection effects is stimulus and mask design. Some participants commented on strategies used in the discrimination task, indicating that alternate approaches to masks and stimuli may produce different results. In line with results from the Visibility Task showing participants were more likely to distinguish photos than polygons, some participants reported using hairstyles to distinguish between photos. Therefore for some stimuli, including naturalistic photographs of humans, simple pattern sandwich-masking may not be sufficient to conceal the item. An alternative approach is to crop images to include facial features only (which we adopted in the next study) and/or to use a composite backward mask, e.g. [Khalid et al. 2013]. We therefore ran a follow-up experiment, 6.3B, to remedy some of these issues: we increased the mask shown duration to try to reduce visibility; cropped our photo images to include facial images only; altered the polygon mask to a composite mask; and changed Text stimuli to capital letters to increase legibility.

In cases where participants do not correctly identify the target they've been shown, the results of the Preference Task show no evidence that showing the target increases target preference. There is some evidence that showing the target decreases preference for text and photos shown once, although again the marginal R^2 measure (marginal R^2=.05) indicates that the amount of variance explained by our fixed effects (*Repetitions Group* and *Stimulus Type*) seem to be small. Further, our estimated marginal means plot shows that the variance in the fixed effects was high (large CI bars).

LIMITATIONS

As with other research into subliminal research focusing on establishing an indirect effect (preference) without a direct effect (visibility) [Greenwald and Draine 1997], the study is limited by using self-reports from participants on visibility of stimuli to indicate whether stimuli were indeed visible. For text stimuli, the words were not balanced for frequency-of-occurrence in the English language or valence, nor were participants limited to native English speakers (75% of participants were native English speakers). Participants were also not screened for dyslexia. These factors may have a confounding effect on subsequent preference judgements, although the stimuli sets were randomised to counter this. Our data for the Preference Task had a low *n* compared to the Visibility

Task (722 vs 4032 trials), and only featured trials from 53 participants, and therefore had reduced power compared to the Visibility Task analysis.

Our low R^2 figures indicate our experiment was noisy. Therefore, in our next experiment 6.3B we altered the experiment design to try to reduce noise. In this, all participants answered the Visiblity Task first, then the Preference Task, rather than randomising the order, and use a fixed stimulus list so that all participants (except the control) see the same stimuli and Tasks in the same order. We also increased the number of repetitions in the multiple-exposure condition to try to amplify any effect.

Experiment 6.3B follow-up

Motivation

To address some of the possible limitations from experiment 6.3, we conducted a follow-up to try to improve the concealment of stimuli and to reduce noise.

Method

Design

We re-ran the experiment study with the following alterations to try to improve stimulus concealment for the visiblity task and to reduce noise:

- Stimuli changes:
    - Face stimuli – added a circle mask to conceal hairstyles
    - Text stimuli – changed to capital letters to improve legibility
- Masks changes:
    - Mask length increased to 200ms to try to reduce visibility further
    - Altered the polygon mask to a composite after we found that a longer mask duration with the existing mask made the polygons visible
- Experiment changes:
    - We added a fourth repetitions condition, visible, where stimuli appeared for 500ms to provide an additional indicator of participant preference where stimuli were visible. We renamed this independent variable Exposure Group. As before, this was between-subjects.
    - Increased number of repetitions in the multiple repetition condition to 5

- In each of the 4 exposure groups (control, 1x, 5x, supra), participants were given a selection task first, in which they were asked EITHER “which did you prefer” OR “choose one” immediately after stimulus exposure. All participants were then asked to complete the Visibility Task (indicate which stimulus they thought they’d seen).
- Instead of randomising the Stimulus Type lists for each participant, each participant saw the same list of pre-randomised text, polygons and images.
- The experiment logged all frame times that exceeded 18ms in order to be able to exclude trials that indicated a dropped frame.

Hypotheses

Our hypotheses were similar to the previous experiment, with additions for the supraliminal (visible) Exposures Group condition.

H1: there would be no difference in the probability of participants being able to correctly identify the prime in the Visibility task between Exposure Groups 0x, 1x and 5x (control and subliminal exposures), but that the supra (visible) Exposure Group would show a higher rate of prime identification, with no statistically significant differences in identification between Stimulus Types.

H2: where participants failed the Visibility Task, compared to the control 0x Exposures Group, participants in the other exposures groups would show statistically significant increased selection rates for stimuli they had just been shown, with no statistically significant interactions between Exposures Group and Stimulus Type.

Participants

50 participants (24 women) took part (0x Exposures Group n=14; 1x Exposures Group n=13, 5x Exposures Group n=12, supra Exposures Group n=11). Age data for 26 participants was lost due to a software bug; the remaining participants had an average age of 24.08 years (SD=6.77).

Apparatus

The same experiment phones were used as before, with Wi-Fi again disabled.

Procedure

Participants were approached around the University campus and asked to participate in a 5-minute experiment on our experiment phone. They read a consent form, entered their demographic

information and completed the tasks on the phone. They were shown a debrief screen informing them which exposures group they were in, and for non-control participants, presenting their results in the form of proportion of shown-before stimuli selected at 'seen', and 'choose' or 'prefer' stages.

RESULTS

DATA ANALYSIS

In line with Study 6.3, responses with reaction times less than 200ms (n=39, 1.3%) were removed.

TIMINGS

Of 2879 observations frames, 4 (0.1%) had frames that conformed to the previous definition of a dropped frame (>25ms); these were omitted from the analysis. The results for overall average percentages of correctly selecting the target are shown in Figure 6:14. The data shows that the combination of the new polygon masking procedure and 5 repetitions is problematic: high proportions of polygons were identified by participants in the 5x exposures group (85%) and was relatively high for the 1x exposures participants (68%).

Figure 6:14 Descriptive statistics for correct selection proportions follow up study 6.3B

VISIBILITY TASK

The proportions of correctly identified targets from the Visibility Task are shown in Figure 6:14. To test hypothesis H1, that participants in non-supra conditions would show no difference in identifying the prime, we examined 1499 observations in the visibility task from 50 participants (14 Control, 13 1x, 12 5x, 11 Supra). Our dependent variable was the binomial correct identification (correct or not); our independent variables were exposures group (control, 1x, 5x and supra, between-subjects) and stimulus type (polygons, photos and text, within-subjects). We tested our hypothesis with a GLMER model with a random intercept for each item (R^2_M=.41, R^2_C=.42) to examine the impact of exposures group and stimulus type on the binary dependent variable of correct identification of the prime. As before, exposure group of 0x repetitions was the baseline. We selected text as the baseline stimulus type instead of polygons as before to investigate the high proportions of polygon selections shown in Figure 6:14. The model included a random intercept for item because including a random intercept for user only accounted for a very small proportion of the residual variance.

Table 6:15 shows a summary of the results. Note that the *p* values are not Bonferroni-corrected, although in this instance it would not make a difference to the statistical significance of the 5xPolygon interaction (*p*<.001, Bonferroni-corrected critical *p* =.004).

	Visibility			
Fixed effects	*Estimate*	*Standard Error*	*Wald z*	*p value*
(Intercept)	-0.15	0.19	-0.77	.44
1x	0.08	0.25	0.34	.74
5x	0.32	0.25	1.25	.21
Supra	4.87	1.02	4.78	<.001
Polygon	-0.15	0.27	-0.55	.59
Photos	0.12	0.27	0.44	.66
1x:Polygon	0.89	0.35	2.52	.01
5x:Polygon	1.61	0.39	4.11	<.001
Supra:Polygon	-1.50	1.13	-1.33	.18
1x:Photos	0.04	0.35	0.12	.91
5x:Photos	-0.52	0.36	-1.47	.14
Supra:Photos	-2.13	1.10	-1.92	.05

Random effects	*SD*
Item (intercept)	0.26

*Model formula: correct ~ exposures group * stimulus type + (1|item)*

Table 6:15 Visibility task log likelihood results for follow up study 6.3B

The results show evidence of positive statistically significant simple main effect of the supraliminal exposures group on the log odds of selecting the primed target (b=4.87, SE=1.02, z=4.78, p<.001) but no other exposures group simple main effects. However, this effect is superseded by the higher-order statistically significant 1xPolygon and 5xPolygon interactions.

The model shows a statistically significant increase in the log odds of selecting the primed target for the 1x and 5xPolygon (b=0.89, SE=0.35, z=2.52, p =.01 and b=1.61, SE=0.39, z=4.11, p<.001 respectively), compared to the baseline control and text conditions. There is no evidence that our new Photo stimuli are detected differently at 1x and 5x repetitions relative to control and the Text baseline (p=.91 and p=.14 respectively), but our changes to the Polygon mask have made them more detectible, relative to the Text baseline. This can also be seen in Figure 6:14 and in the estimated marginal mean probability figures given in Figure 6.16.

Exposures Group	*Stimulus Type*	*Estimated marginal probability %*
Control	Text	46.4
	Photos	49.3
	Polygon	42.7
1x	Text	48.4
	Photos	52.4
	Polygon	66.4
5x	Text	54.2
	Photos	44.1
	Polygon	83.5
Supra	Text	99.1
	Photos	93.8
	Polygon	95.6

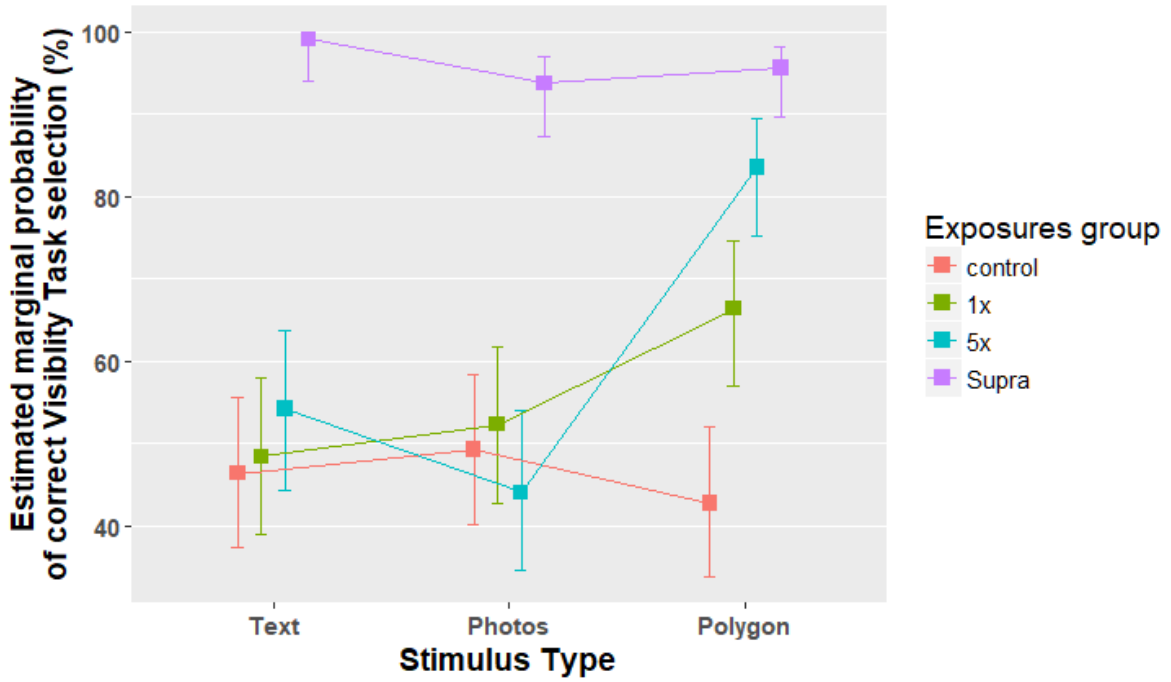


Figure 6.16 Estimated marginal means probability plot and values of Visiblity Task responses correctly identifying the prime

SELECTION TASKS

Descriptive statistics for our two preference tasks, Choose and Prefer, are shown in Figure 6.17. As can be seen in the charts, there were no data for choose or prefer 5xPolygons or Supra:Polygons conditions or Supra:Text, i.e. there were no trials for these combinations where the user got the visibility task wrong.

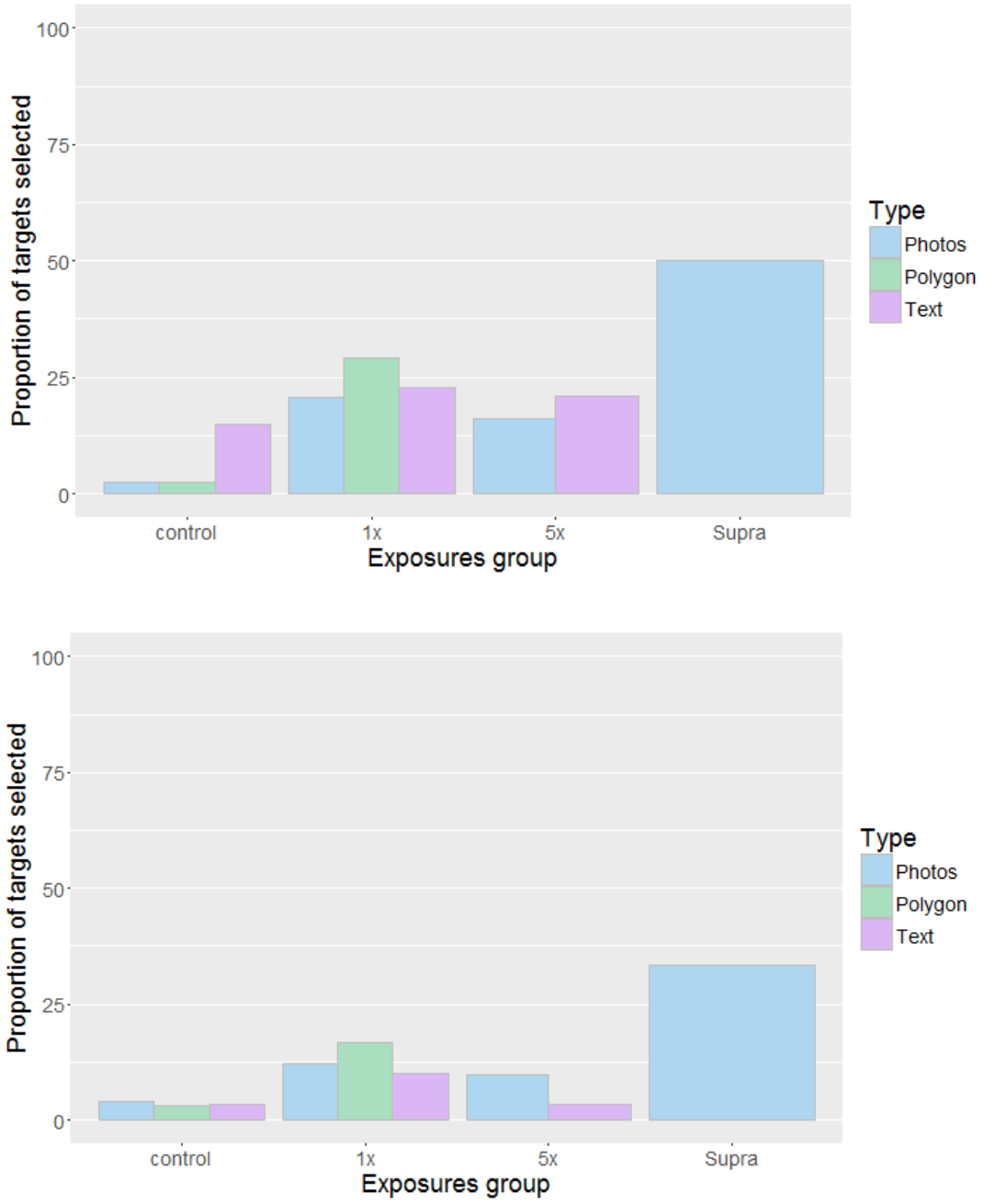


Figure 6.17 Preference task selections where visibility task was failed (top) Prefer task, (bottom) Choose task

The selection tasks show similar patterns for choose and prefer, although overall prefer rates were lower. To investigate our hypothesis H2, that participants in the 1x, 5x and supra exposures groups would have a statistically significant higher rate of Prefer and Choose Task selection compared to the control 0x participants, regardless of stimulus type, we constructed a GLMER for each of the "Prefer" and "Choose" data sets where participants had answered the visibility task incorrectly. The GLMERs examined the effect of exposures group (control, 1x, 5x and Supra) and stimulus type (polygon,

photo and text) on our dependent binomial variable, correct selection of the target (0 or 1). We were unable to run the analysis because the very high numbers of correct answers meant insufficient data to model selection choices where participants were unable to detect the prime. This also can be seen in the missing data in Figure 6.17. The missing data means we are unable to compare switching across visibility conditions (0 and 1). i.e. the tendency for participants to select opposite answers in visibility and preference trials. Instead, we ran a GLM[8] (R^2_{PS} = 0.75) to analyse the 944 trials where the target was correctly selected in the visibility task. We examined the effect of exposure group (control, 1x, 5x and Supra, control as baseline) and stimulus type (Text, Photos, Polygons, text as baseline) on the subsequent selection of target (correct or not, incorrect as baseline), with the model results given in Table 6:16 and the model's estimated marginal means plot given in Figure 6.18. Note that the *p* values are not Bonferroni-corrected.

Fixed effects	*Estimate*	*Standard Error*	*Wald z*	*p value*
(Intercept)	*2.72*	*0.52*	*5.28*	*<.001*
1x	*-1.28*	*0.61*	*-2.10*	*.04*
5x	*-1.24*	*0.61*	*-2.04*	*.04*
Supra	*15.84*	*624.76*	*0.03*	*.98*
Photos	*-0.54*	*0.65*	*-0.83*	*.40*
Polygons	*0.64*	*0.89*	*0.73*	*.47*
1x:Photos	*0.74*	*0.80*	*0.93*	*.35*
5x:Photos	*1.12*	*0.85*	*1.32*	*.19*
Supra:Photos	*-14.11*	*624.76*	*-0.02*	*.98*
1x:Polygons	*0.19*	*1.01*	*0.19*	*.85*
5x:Polygons	*1.34*	*1.11*	*1.21*	*.23*
Supra:Polygons	*-14.56*	*624.76*	*-0.02*	*.98*
*Model formula: select ~ exposure group * stimulus type*				

Table 6:16. Selection switch analysis, results summary

The results show evidence of similar statistically significant simple main effects for 1x and 5x exposure group conditions; both had a negative impact on the log odds of the response to the preference task matching that of the visibility task compared to the baseline, indicating a higher tendency to switch for these conditions (1x *b*=1.28, *SE*=0.61, *z*=2.10, *p*=.04; 5x *b*=1.24, *SE*=0.61, *z*=2.04, *p*=.04). There is no evidence of a statistically significant difference for supra exposures group reactions either as a simple main effect (*p*=.98) or as interactions with different stimulus types (Supra:Photos *p*=.98; Supra:Polygons *p*=.98), but there is a high standard error for supra conditions,

[8] Models with random effects included did not converge. Our R^2_{PS} for the GLM was that of Nagelkerke [Nagelkerke 1991] , calculated using the modEvA package [Barbosa et al. 2016].

reflecting the lack of data for switching selection once visibility was correct. The intercept of the selection model is statistically significant even at Bonferroni-corrected *p* values, which indicates that overall for the baseline condition (control, text), selection responses tended to agree with the visiblity selection: regardless of priming, people tended to stick with their first answer. This can also be seen from the EMM probabilities given in Figure 6.18. Note that the 95% Cis for the Supra Text condition could not be calculated due to missing data.

Exposures Group	*Stimulus Type*	*Estimated marginal probability*
Control	Text	93.8%
	Photos	89.9%
	Polygon	96.7%
1x	Text	81.0%
	Photos	83.8%
	Polygon	90.1%
5x	Text	81.5%
	Photos	88.7%
	Polygon	97.0%
Supra	Text	100%
	Photos	98.0%
	Polygon	99.0%

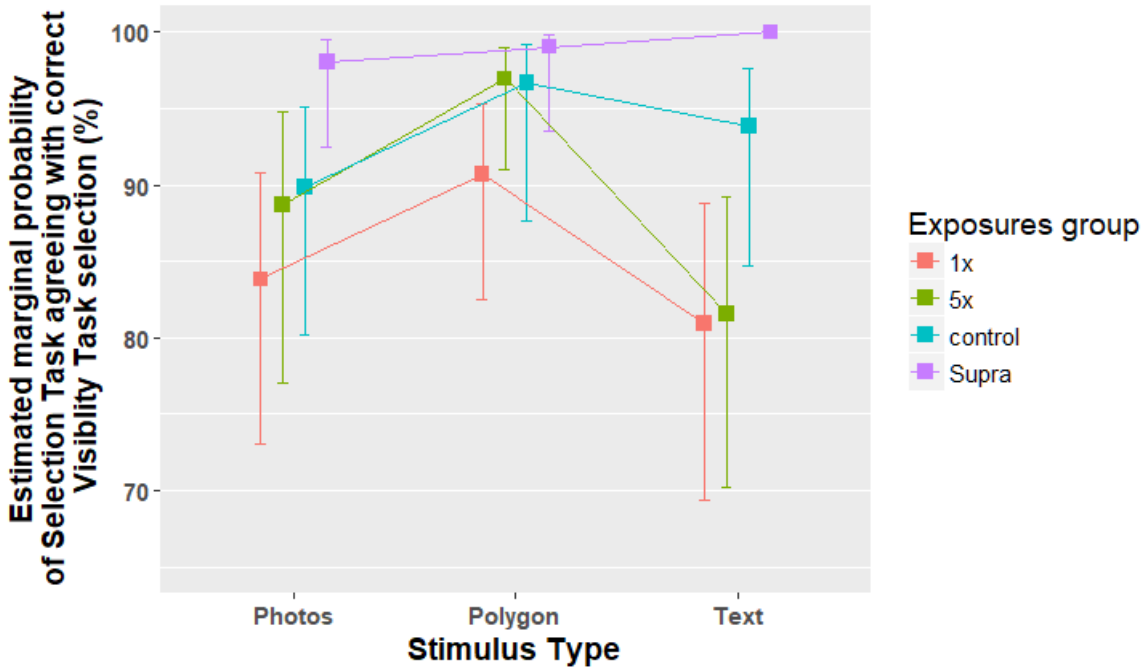


Figure 6.18 Estimated marginal means probability of Selection Task response agreeing with visibility task response where visibility task was correct by stimulus type and exposures group condition with 95%CIs

Discussion and limitations

Our adjustments to the polygon masks as a follow-up to Experiment 6.3 made them more visible, not less as had been our intention. This indicates some fragility in the masking procedures to make stimuli not accessible to conscious perception. Further, the high proportions of supraliminal stimuli subsequently selected in the Prefer and Choose tasks prompts the question of how to determine the situations in which subliminal priming should be used instead of supraliminal priming on smartphones. Even where differences exist, they are of limited practical use – e.g. for 1x and 5x, stimulus exposures that are correctly identified seem to have a negative impact on their subsequent preference selection, although the estimated differences are around 10 percentage points.

Experiments 6.3 and the follow-up also restrict processing of the stimuli to a recognition factor. A more fundamental question, which we address in the next experiment, is whether subliminal perception can extract *meaning* from stimuli.

Experiment 6.4: Subliminal semantic number processing on smartphones

Motivation

We wanted to investigate whether there is any evidence of *semantic* priming, i.e. that people can extract *meaning* from subliminal primes despite not being able to identify them. If such meaningful transfer of information is possible, then it is evidence of cognitive activation of concepts related to the prime, over and above simple stimulus-response learning. This activation opens up the possibility of subliminal priming placing items on the Potential Behavioural stack in the BAF, thus increasing the likelihood of the related behaviour occurring without increasing cognitive load.

We based this experiment on a psychology experiment exploring subliminal semantic priming effects [Ocampo 2015]. The aim was to understand the impact of novel (i.e. not-seen-before) subliminal primes on free choices. In contrast to previous experiments in this chapter, where all primes appeared as targets in subsequent 2-alternative-forced-choice questions, this experiment used some novel primes that never appear supraliminally as targets. This allowed us to determine whether responses are based on some semantic processing of the concealed prime: response to *novel* primes indicate some level of semantic processing.

Method

HYPOTHESES

Our experiment addresses three research questions: (RQ1) can people consciously recall concealed number primes on smartphones; (RQ2) are these concealed number primes processed on a semantic level with different effects for novel and repeat primes; (RQ3) can these concealed number primes affect people's free choices, and is that effect different between repeat and novel primes. We use novel and repeat primes, since repeat primes may have an effect via stimulus-response implicit mappings, while novel primes instead may only have an effect via semantic or meaningful cognitive processing. Our related hypotheses, in line with Ocampo [33], are:

H1: the probability of participants correctly identifying concealed primes would be no better than chance. This would suggest that people could not see the concealed primes on smartphones (RQ1)

H2: forced-choice (a) reaction times and (b) accuracy rates would be affected by prime congruence with no difference between novel and repeat primes. This would suggest that semantic processing of primes is as efficient in terms of accuracy and reaction time as stimulus-response processing (RQ2).

H3: free-choice (a) reaction times for responses would be faster for responses in line with prime, with no differences for either novel and repeat primes; and (b) selections would be in line with prime with no impact of novelty. This would suggest that subliminal semantic priming can affect user's free choices in similar ways as stimulus-response priming (RQ3).

PARTICIPANTS

103 people (age: mean= 24.57 years, SD= 4.08; 38 women) completed the experiment. 8 had completed a previous subliminal experiment (6.3 or a follow-up). We used the same-batch experimental phones as before.

PROCEDURE

Participants were approached on campus and asked to participate in a number sorting task. They read a consent screen which informed them that the aim of the task was to categorise numbers as less than or more than 5, completed a demographics questionnaire, and a brief practice run.

Next, participants completed 576 response task trials. A response task trial required looking at a smartphone screen with a display area for a stimulus (the *target*- either a number or a symbol), and two buttons below, as shown in the screenshot in Figure 6.19.

The left-hand button was marked with the less than symbol “<”; the right button was marked with the more than “>” symbol. In each trial, following a forward mask, a number prime, and a backward mask, a *target* appeared in the display area. Target stimulus was randomly either a number (forced choice trials) or a “#” symbol (free choice trails). If the *target* stimulus was a number, participants were asked to use the left or right button to indicate whether the number was greater or less than 5. We recorded reaction times as one outcome variable. Forced-choice trials in which participants correctly identified whether the target was greater or less than 5 were categorized as *correct* with others categorized as *incorrect*. This forms a binary accuracy outcome variable for the forced-choice trial analysis below.

If the target stimulus was the “free choice” symbol “#”, they were asked to respond freely using either button. Participants were asked to avoid using a set response scheme (e.g. “always left”) to respond to the free choice symbol “#”. We recorded reaction times as one outcome variable. Trials in which participants chose the button that corresponded to the prime were categorized as agreeing, with others categorized as not agreeing. This forms a binary outcome variable for the free-choice trials analyses below.

Two-thirds of the 576 trials had a number as a target, one-third were free choice trials. Half of the number trials had a congruent prime (i.e. the same side of 5 as the target); half had an incongruent prime (i.e. the opposite side of 5 as the target). 50% of all trials used a *novel* prime number as a prime, i.e. a number that never appeared as a target. Numbers 1,4,6 and 9 appeared both as targets and repeat primes; numbers 2,3,7 and 8 appeared as novel primes only. Masks were randomly generated 30x30 pixel black backgrounds with multiple overlapping letters in white, with different forward and backward masks. Numbers appeared in white Verdana font size 20 on a 30x30 black background. We used this sans-serif font at size 20 because of evidence that sans-serif fonts and font sizes greater than 18pts are more accessible for people with dyslexia [Rello et al. 2013; Rello and Baeza-Yates 2013], and therefore suitable for a more accessible intervention should the technique be shown to be successful.

The procedure is shown in Figure 6.19.

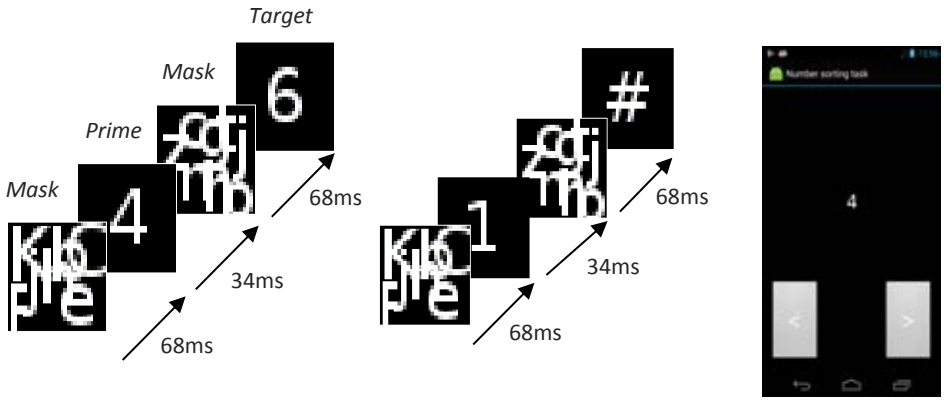


Figure 6.19 Experiment procedure (left) incongruent repeat forced-choice trial, (centre) free choice trial, and (right) experiment screenshot

Participants were given 1.5 seconds to respond, and the app informed them if they got the answer wrong or they timed out. The prime appeared for 2 frames, approximately 34ms on our experiment phones, and masks appeared for 4 frames, approximately 68ms, in line with the original experiment (masks ~70ms, primes ~33ms). Targets were displayed for ~203ms. Trials were split into 3 blocks, with a chance to rest in between.

After completing these 576 *response task* trials, participants were informed of the existence of the subliminal prime. They then completed 144 *visibility trials* with the same stimulus proportions as the response task. In visibility trials, participants were asked to try and identify the *prime* by answering whether the prime itself, and not the target as in previous trials, was greater than or less than 5.

Table 6:17 shows a summary of our independent variables (IVs) and dependent variables (DV) for the three trial types (visibility, forced-choice and free-choice).

Trial type	*DV*	*IVs*
Visibility (RQ1)	Response (binomial, more than or less than)	Prime value (binomial, more than or less than)
Forced-choice (RQ2)	Response time (continuous, ms)	Congruence (congruent or incongruent primes) Novelty (repeat or novel primes)
Forced-choice (RQ2)	Correct selection of target (binomial, correct or incorrect)	Congruence (congruent or incongruent primes) Novelty (repeat or novel primes)
Free-choice (RQ3)	Response time (continuous, ms)	Novelty (repeat or novel primes)
Free-choice (RQ3)	Agreement with prime (binomial, yes or no)	Novelty (repeat or novel primes)

Table 6:17 Experiment trials variables summary

Results

DATA CLEANING & SUMMARY

The final analysis included 72,720 trials from 101 participants after one participant was excluded because they recorded more than the 720 trials, and one was excluded because they did not complete all the trials. Trials where the participant timed out were then excluded (394 trials, 0.54%), as were trials where frame timing errors indicated a potential problem, i.e. a dropped frame of > 25ms was recorded (22 trials, 0.28%). In contrast to Experiments 6.3 above, we retained trials with reaction times less than 200ms (n=6435) in case fast responses capture primed responses, since the responses did not switch sides.

Descriptive statistics for reaction times for 38,450 forced-choice tasks by congruent group (congruent, incongruent) and novelty of prime (repeat, novel) are shown in Table 6:18 and Figure 6.20.

Group	*Prime type*	*Mean*	*SD*
Congruent	*Novel*	560.08	138.00
	Repeat	607.59	145.73
Incongruent	*Novel*	560.41	141.99
	Repeat	562.04	141.48

Table 6:18 Forced-choice descriptive statistics for response task RTs congruence~novelty in milliseconds

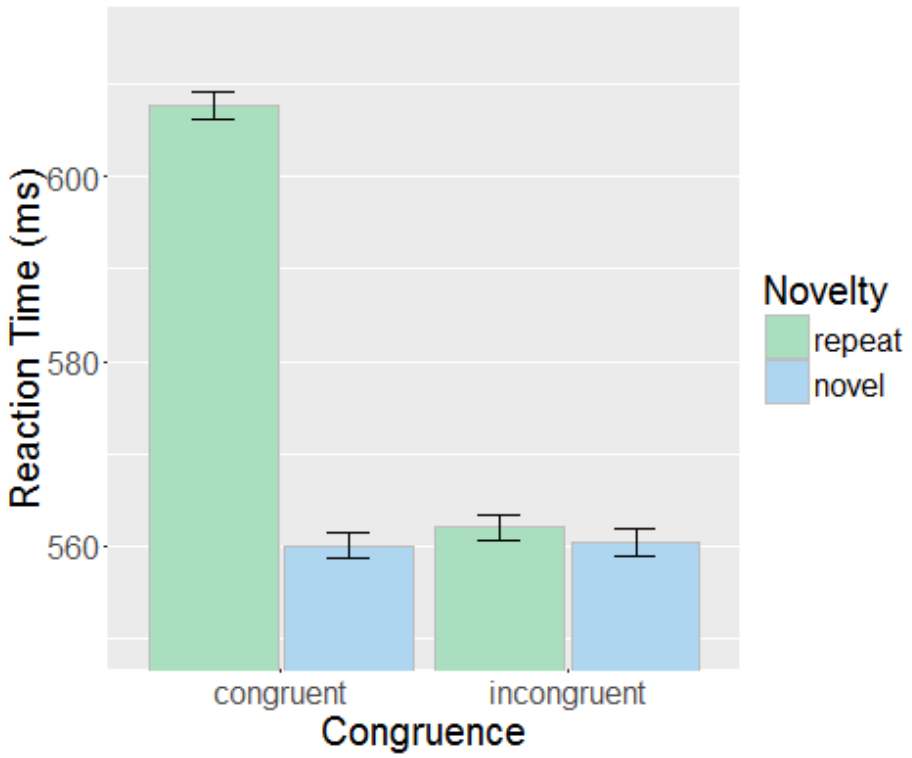


Figure 6.20 Forced-choice RTs congruence * novelty in ms barplot with 1 SE error bars

This shows that responses to Congruent Repeat primes had on average a slower reaction time of around 47ms, with no overlap of confidence intervals (approximately 2x the 1SE error bars shown, see discussion on p 4:64), and little difference between the other conditions with responses around the 560ms mark.

Table 6:19 shows descriptive statistics for the overall percentage of forced-choice trials that correctly identified the target number as more or less than 5, grouped by prime congruence and novelty.

Group	*Prime type*	*Mean %*	*SD*
Congruent	*Novel*	87.54	8.31
	Repeat	88.29	7.83
Incongruent	*Novel*	87.15	8.48
	Repeat	87.03	7.60

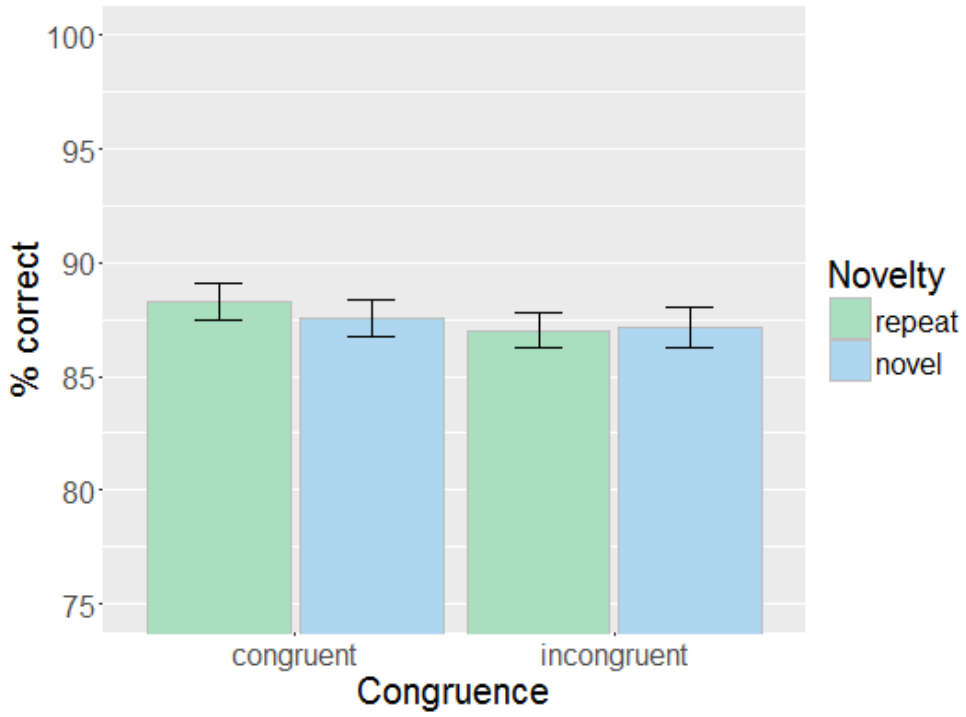


Table 6:19 Forced-choice descriptive statistics for correctness with 1SE error bars

The data shows little difference between the conditions if we consider CIs of 2x the 1 SE error bars shown (see discussion on page 4:61).

Descriptive statistics for the percentage of free choice trials that agreed with the prime, grouped by whether the prime was novel or not, are shown in Table 6:20.

Group	*Mean*	*SD*
Novel prime	50.47%	5.08
Repeat prime	53.32%	7.69

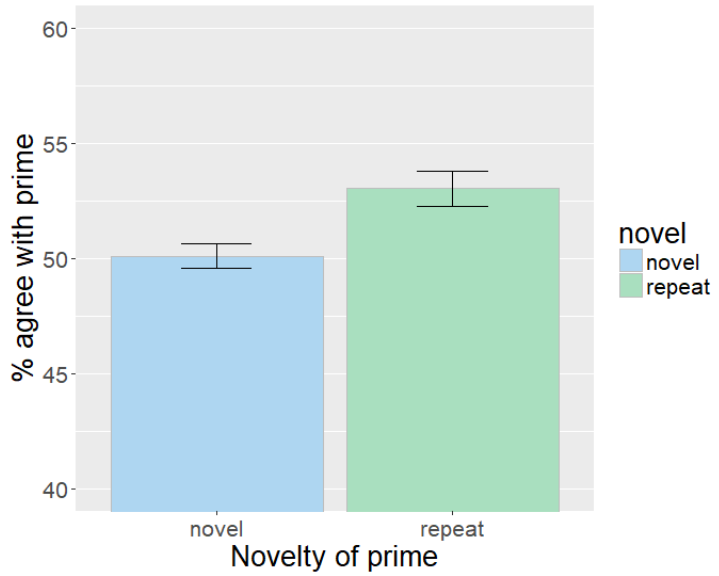


Table 6:20 Free choice agreement with prime by prime novelty

The data shows little difference between the conditions if we consider CIs of 2x the 1 SE error bars shown (see discussion on page 4:61).

Descriptive statistics for the 14,544 Visibility Task trials are shown in Table 6:21. “Correct” trials are ones in which participants correctly identified whether the prime was greater or less than 5, regardless of the target.

Group	*Mean % correct*	*SD*
Novel prime	50.94	5.71
Repeat prime	49.33	5.94

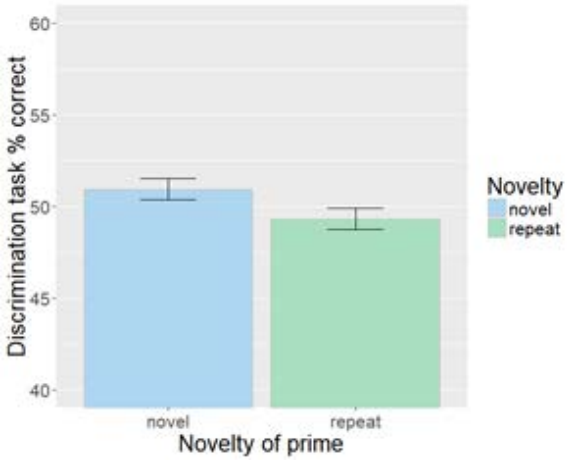


Table 6:21 Visibility task %correct trials by prime novelty

Again, the data shows little difference between the conditions if we consider CIs of 2x the 1 SE error bars shown (see discussion on page 4:61).

DATA ANALYSIS

In contrast to our previous (G)LMER models, we used deviation coding since there is no clear ‘baseline’ for our factors, and to ease comparison with the original experiment. This means the intercept of each model represents the grand mean, rather than the mean of the baseline factors.

VISIBILITY TASK

To examine hypothesis H1, that participant ability to identify concealed primes would be no better than chance, we examined the data from Visibility Trials conducted after participants had been informed of the nature of the experiment using GLMER. We removed 1 participant with an outlying same-response rate. For the remaining 14,313 trails, our model analysed whether the binomial participant response (more than or less than) could be predicted by the prime value (more than or less than), allowing for a random by-participant intercept. The model (R^2_M=<.001, R^2_C=0.03) results are shown in Table 6:22. Note that the *p* values are not Bonferroni-corrected, although in this

instance the corrected *p* value would not change the statistical significance (corrected for 2 comparisons, critical *p* = .025). They show that although overall there was a statistically significant positive intercept, indicating an overall pattern of selecting the "more than" answer at a higher rate than "less than" answer (*b*=0.10, *SE*=0.03, *z*=3.44, *p* = <.001), there was no evidence that prime direction affected the likelihood of particular responses (*p* = .36). This supports our hypothesis H1.

	Visibility task			
Fixed Effects	*Estimate*	*SE*	*Wald z*	*p value*
(Intercept)	0.10	0.03	3.44	<.001
Direction	-0.02	0.02	-0.91	.36
Random Effects			SD	
Participant (intercept)			0.30	
Model formula: response ~ prime direction + (1 | participant)				

Table 6:22 Visibility Task model results

FORCED-CHOICE TASK

To examine H2, we removed the data of 2 outlying participants who responded with the same response more than 65% of the time (759 trials, 1.97%). To examine the first part of hypothesis H2, that reaction times for correct responses would differ for congruence and novelty, we constructed a GLMER model to analyse raw reaction time data and allow for within-participant variation. This contrasts with the ANOVA used on mean values in the original study [23].

Our model analysed the effect on reaction time of prime congruence (congruent or incongruent) and prime novelty (repeat or novel), and included a per-participant random intercept. We removed 1020 trials (3.71%) based on model residuals. For the remaining 36,671 trials, the model that converged (R^2_{ps}= 0.27) included a per-participant random intercept.

The results are shown in Table 6:23. Note that the *p* values are not Bonferroni-corrected, although in this instance the corrected *p* value would not change the statistical significance (corrected for 4 comparisons, critical *p* = .0125).

Fixed Effects	*Estimate*	*SE*	*t*	*p value*
(Intercept)	588.91	4.44	132.52	<.001
Congruence	12.11	0.49	24.66	<.001
Novelty	13.19	0.49	26.92	<.001
Congruence:Novelty	11.76	0.49	24.00	<.001
Random effects	*SD*			
Participant (intercept)	19.99			
Residual	0.01			

*Model formula: RT ~ congruence * novelty + (1 | participant)*

Table 6:23 Forced-choice reaction time model results

The results show a statistically significant interaction between congruence and novelty (b=11.76, SE=0.49, p <.001). This is also shown in the barplot in Figure 6.17 and in the model's estimated marginal mean RTs and 95%CIs in Figure 6.18. Congruent repeat primes (estimated RT=626ms) are estimated to have a slower response time than both congruent novel primes (576ms) and incongruent repeat primes (578ms).

	Prime novelty	
Prime congruence	Novel	Repeat
Congruent	576.1	626.0
Incongruent	575.4	578.2

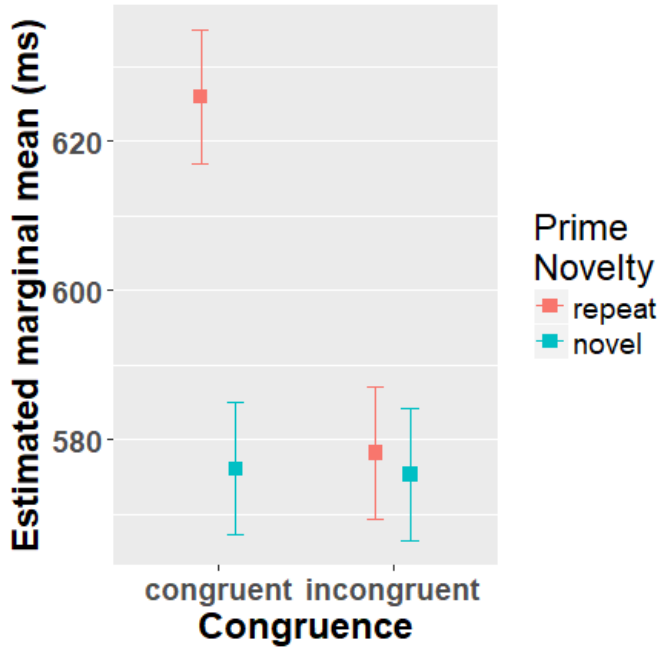


Figure 6.18 Estimated marginal mean forced-choice task RTs (ms) and plotted with 95%CIs

These results contrast with those from the lab: Ocampo found with a 2x2 ANOVA only a statistically significant main effect of congruence (p < .001, d=.96), where incongruent responses were slower, and no evidence of a statistically significant novelty main effect or congruence -novelty interaction [2015]. Our results instead suggest that where primes are congruent (prime and target are both either above or below 5, so the prime provides pertinent information about the target), people were

faster at responding where the primes were *novel* (indicating some semantic processing) compared to where the primes were *repeat* (indicating some stimulus-response processing), although the difference is small (~50ms).

To examine the second part of H2, that forced-choice correct target selection would be influenced by prime congruence, we used a logistic regression GLMER model to analyse the effect on correct selection of (correct or not) of prime congruence (congruent or incongruent) and prime novelty (repeat or novel), with a per-participant random intercept.

Fixed Effects	*Estimate*	*SE*	*Wald z*	*p value*
(Intercept)	2.16	0.08	26.14	<.001
Congruence	0.04	0.02	2.50	.0126
Novelty	0.02	0.02	0.98	.33
Congruence:Novelty	0.02	0.02	1.34	.18
Random Effects	*SD*			
Participant (intercept)	0.80			
*Model formula: correct ~ congruence * novelty + (1 | participant)*				

Table 6:24 Forced choice task agreement model results

The model (R2M <0.01, R2C = 0.16) results are shown in Table 6.24. Note that the *p* values are not Bonferroni-corrected. The results show that there is evidence of a small statistically significant main effect of congruence on the log odds of correct selection (*b*=0.04, *SE*=0.02, *z*=2.50, *p*=.01), but no other main or interaction effects. This is in line with Ocampo's findings of a main effect of congruence and no other statistically significant effects on correct selection [Ocampo 2015]. Congruent primes, i.e. the prime is on the same side of 5 as the target number, are estimated to improve the correct categorisation of the number as above or below five on average by a very small amount, less than 1 percentage point, with overlapping confidence intervals, as shown in the estimated marginal probability of correct categorisation of target in Table 6:25.

Prime type	*Estimated marginal probability %*	*95%CI*
Incongruent	89.3	[88.2,91.2]
Congruent	90.0	[87.9,91.0]

Table 6:25 Forced choice agreement estimated marginal probability of correct categorisation

FREE-CHOICE TASK

Next, we addressed RQ3. We hypothesised that people's free choices (i.e. their response to the # symbol, the binomial response variable "more than" or "less than") would be influenced by the concealed primes. We examined the data from the free-choice task and removed trials from 6

participants who responded with the same answer more than 80% of the time. A barplot with reaction times from the remaining 18,084 trials are shown in Figure 6.21.

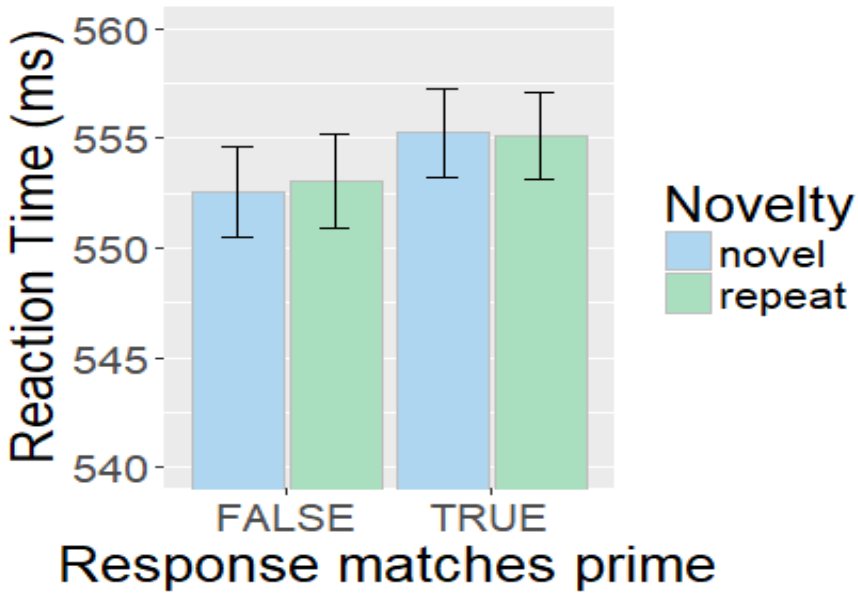


Figure 6.21 Free trial RT by novelty and agreement barplot with 1SE error bars

Figure 6.22 shows a barplot for agreement by novelty.

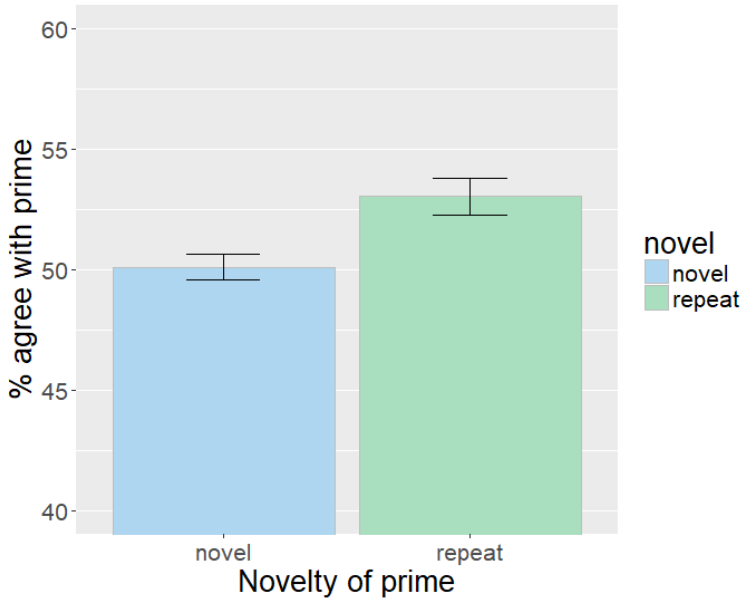


Figure 6.22 Free trial agreement by novelty barplot with 1SE error bars

For hypothesis H3(a), that reaction times for responses would be faster for responses in line with prime, with no differences for either novel and repeat primes, we constructed a GLMER model to

analyse whether *novelty* (novel or repeat) x *agreement* (free choice agreed with prime or not) affected reaction time, with a by-participant random intercept. We trimmed 573 trials (3.17%) based on model residuals. The model that converged (R^2_{PS} = .37) is summarised in Table 6:26. Note that the *p* values are not Bonferroni-corrected, although in this instance the corrected *p* value would not change the statistical significance (corrected for 4 comparisons, critical *p* = .0125).

	Free choice RT			
Fixed effects	*Estimate*	*SE*	*t*	*p value*
(Intercept)	567.98	5.88	96.56	<.001
Novelty	-0.09	0.59	-0.16	.87
Agreement	1.11	0.59	1.86	.07
Novelty:Agreement	-1.55	0.60	-2.61	.009
Random effects		*SD*		
Participant (intercept)		22.77		
Residual		0.01		

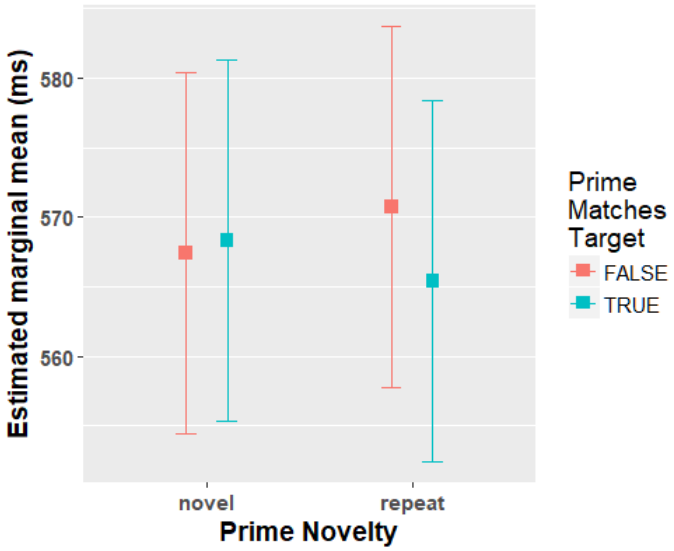
Model formula: RT ~ novelty*agreement + (1 |participant*)*

Table 6:26 Free-choice RT model results

As hypothesised, there was no evidence of a main effect of novelty (*p*=.87), but no evidence of an expected main effect of agreement (*p*=.07), and the results also showed a very small statistically significant interaction between novelty and agreement (*b*=1.55, *SE*=0.60, *t=2.61*, *p*=.01).

The estimated marginal mean RTs in Figure 6:27 indicate that the model predicts a very small crossed interaction effect: for novel primes, responses that agree with the prime are predicted to be slower than disagreeing answers by less than 1ms, with the opposite pattern for repeat primes, where agreeing responses were faster by around 5ms.

Again, our results contrast with those from the lab: Ocampo found no statistically significant main effect of novelty on free choice reaction time, but found a statistically significant main effect of agreement (faster RTs for agreement). No interaction significance was reported. Instead, we found that agreeing responses for repeat primes were faster, compared to agreeing responses for novel primes.



Prime Novelty	*Prime matches target*	*EMM*	*95%CI*
novel	FALSE	567	[554,580]
	TRUE	568	[555,581]
repeat	TRUE	565	[552,578]
	FALSE	571	[558,584]

Figure 6:27 Free trial model estimated marginal means (EMM) plot and data

To investigate hypothesis H3(b), whether the prime and prime novelty affects participant free choices, we used a logistic GLMER on the trimmed data to analyse the effect of the prime *value* (more than or less than 5) and prime *novelty* (novel or repeat) on participant response (whether they responded in the same direction as the prime, yes or no). The model included a by-participant random intercept as a random effect. The model (R^2_M = .01, R^2_C = .02) results are shown in Table 6:28. Note that the *p* values are not Bonferroni-corrected, although in this instance the corrected *p* value would not change the statistical significance (corrected for 4 comparisons, critical *p* = .0125).

The model showed no statistically significant prime direction x novelty interaction effect (p=.37), but showed both a statistically significant effect of prime value (*b*=0.36, *SE*= 0.03, *z*=11.85, *p*<.001), and a smaller statistically significant main effect of prime novelty (*b*=0.07, *SE*=0.02, z=3.40, *p* <.001) on the log odds of the participant matching the prime.

	Free choice matches prime			
Fixed Effects	*Estimate*	*SE*	*Wald z*	*p value*
(Intercept)	-0.10	0.03	-3.68	<.001
Novelty	-0.07	0.02	-3.40	<.001
Value	0.36	0.03	11.85	<.001
Value:Direction	0.03	0.03	0.90	.37
Random Effects	*SD*			
Participant (intercept)	0.14			
*Formula: agreement ~ novelty * value + (1 | participant)*				

Table 6:28 Free choice task agreement results

Considering the main effect of prime value, there is evidence that participants had a higher probability of agreeing with the prime when it was more than 5 (56.6%) than when it was less than 5 (47.6%) as shown in Table 6:28. This may indicate some default tendency of participants to select the "more than 5" or right-hand answer overall.

In terms of prime novelty, our model indicates a statistically significant impact of novelty on agreement. There was a small increase in the estimated marginal mean probability of participants agreeing with the primed response in the repeat primes condition (53.6%), compared to the novel primes condition (50.7%) as shown in Table 6:29. Although there is a smaller probability of agreement for novel primes, these probabilities are close to what would be expected by chance.

Prime value	*EMM probability %*	*95%CI*
Less Than 5	47.6	[46.3, 48.9]
More Than 5	56.6	[55.4, 57.9]

Prime novelty	*EMM probability %*	*95%CI*
Novel	50.7	[49.4, 51.9]
Repeat	53.6	[52.3, 54.8]

Table 6:29 Free-choice agreement model EMM probability of agreement for levels of prime value and prime novelty

Again, these results contrast with those from the lab. Ocampo found a statistically significant overall positive trend for participants to select the primed response, which we did not, but no evidence of the impact of novelty. Our results indicate a statistically significant impact of novelty, with a small increase in the log odds of a participant selecting the primed response with repeat primes compared to novel primes, and a statistically significant impact of prime value, with an increase in the likelihood of correctly selecting "more than" responses compared to "less than" responses. This may indicate a default tendency for participants to favour a "more than" selection in general, regardless of prime. Once more, our R^2 values are small, requiring caution in interpreting the model results.

Discussion

Our results are summarised in Table 6:30.

Our aim was to determine whether participant responses were based on some semantic processing of our concealed primes. Responses to novel primes indicate some level of semantic processing, whereas responses to repeat primes may indicate basic stimulus-response priming. Participants completed three sets of tasks; forced-choice tasks in which they were shown a prime, then a target and asked to respond whether the target was greater than or less than 5 (with reaction time and correct-answer dependent variables); free-choice trials where they were shown a prime and a symbol target and asked to respond freely greater than or less than (with reaction time and agreement-with-prime dependent variables); and finally a visibility task after the presence of primes

had been revealed where they were asked to respond whether the prime, not the target, was greater than or less than 5 (with a binomial agreement-with-prime dependent variable).

Trial and hypothesis	Result
Visibility H1	No evidence of visibility (no evidence of impact of prime direction on correct selection).
Forced-choice H2a	No evidence for different impact of semantic processing on accuracy (no evidence of impact of novelty). Evidence of very slightly improved accuracy (<1 percentage point) for congruent primes.
Forced-choice H2b	Evidence of slightly slower stimulus-response processing than semantic processing where primes contain correct information about the target (congruent repeat primes estimated to have a ~50ms slower reaction time than congruent novel primes)
Free-choice H3a	Evidence that stimulus-response processing very slightly improves agreement compared to semantic processing (repeat primes estimated to improve probability of answers matching the prime compared to novel primes by ~3 percentage points to 53.6%).
Free-choice H3b	Evidence that semantic processing is very slightly slower than stimulus-response processing for answers matching the prime (responses to novel primes estimated to be ~3ms slower than repeat primes).

Table 6:30 Results summary

The first research question was whether we can conceal number primes. From the Visibility Task (H1), we found a small statistically significant overall tendency for participants to respond in the "more than" direction, but no evidence of a statistically significant effect according to prime value (more or less than 5). Therefore, there is no evidence to suggest that the primes were visible. This contrasts with some evidence of visibility from the original Ocampo experiment, and our research in experiment 6.3 finding different sorts of primes were visible to a certain extent.

The second question is whether congruent masked primes (i.e. primes that semantically agree with the target) increased agreement and reduced reaction time, and whether this effect differed between repeat and novel primes. Forced-choice categorisation results (H2a) showed a very small statistically significant impact of congruence, where congruent primes slightly improved the probability of correct categorisation of target by <1 percentage point but no evidence of a statistically significant impact of prime novelty. The results from the forced-response task reaction times showed evidence of a statistically significant interaction between congruence and novelty, where congruent repeat primes tended to result in slightly slower reaction times (~50ms) than other conditions.

The third research question was whether the primes affected people's free-choices. Where participants freely chose the answer that matched the prime (H3a), we found a statistically significant main effect of both prime novelty and prime value on participant responses. Repeat

primes statistically significantly improved the probability of answers matching the prime compared to novel primes by ~3 percentage points to 53.6%. This is some evidence that repeat primes may influence free choice to a small extent. How-ever, the evidence is mixed since participants also tended to select one answer (the “more than” answer) rather than the other (the “less than” answer), with a higher estimated selection probability of 56.6%. This may indicate that subliminal priming is insufficient to overcome a user tendency to default to one answer in situations of arbitrary selection such as the free-choice task.

In terms of free-choice reaction times (H3b), there was an interaction effect of *prime novelty* and *agreement* (i.e. answers that matched the prime). The results show that when the answer agreed with the prime, novel primes tended to result in a very slightly slower response (~3ms) than repeat primes. This suggests that semantic processing of novel primes – i.e. so that the participant processed the semantic information in the prime to agree with it - slows reaction times to small extent compared to stimulus-response processing acquired from the repeat primes.

Overall, on the definition of subliminal priming of an indirect effect (our forced-choice and free-choice trials) without a direct effect (our visibility task), there is evidence of subliminal priming impacting user choices to a small extent. Our visibility task showed no evidence that prime value affected selections, i.e. no evidence that participants could detect the prime, while our forced-choice task accuracy showed a very small increase in accuracy (less than 1%) where targets were in line with primes.

The evidence also shows that the impact of *semantic* subliminal processing is inconsistent across free- and forced-choice trials. In free-choice trials, novel primes are estimated to have a smaller impact on correct selection than repeat primes. Prime novelty also impacted on reaction time in the free-choice task, with repeat primes (i.e. those that may not be processed semantically) decreasing correct reaction times compared to novel primes very slightly by ~3ms. Within the forced-choice trials, where primes were congruent with the target, repeat primes increased reaction times slightly by ~50ms. There was no evidence of an impact of prime novelty on correctness in forced-choice trials.

In summary, our results show some evidence of a small trade-off between efficiency metric (speed or accuracy) between stimulus-response and semantic processing (novel or semantic primes) of number primes depending on the task (forced-choice or free-choice). This trade-off is shown in Table 6:31.

	Efficiency metric	
Task	*Speed*	*Accuracy*
Forced-choice	Semantic/novel	Either*
Free-choice	Stimulus-response/repeat	Stimulus-response/repeat

**No evidence of statistically significant difference*

Table 6:31 Efficiency trade-off for semantic vs stimulus-response processing of subliminal primes by task

The results indicate that the appropriate choice of subliminal prime to improve interaction efficiency depends on whether the task is forced choice (e.g. between two fixed options with one correct answer), or whether there is a free choice (no correct answer). For forced-choice trials, if speed is the main efficiency consideration, using novel primes is faster. For free-choice trials, on speed and accuracy grounds, using repeat, stimulus-response processing is more efficient.

However, caution is advised, since the size of the estimates and R^2 values are small: there is little evidence that subliminal priming is an effective way to improve interaction efficiency to any great extent. The evidence shows that using subliminal primes to improve interaction efficiency on smartphones is likely to make little difference. Likewise, given the lack of evidence of any strong semantic priming effects, there is no support for the application of semantic priming in behaviour change applications such as the use of subliminal goal priming of short word phrases. This is consistent with our lack of results from attempts to use subliminal goal priming in-the-wild (Experiment 6.1) .

Our results differed from Ocampo's original lab experiment [Ocampo 2015] in several respects. For visibility, we found no evidence of visibility, while the lab study found that participants' ability to discriminate primes did differ from zero. For free-choice trials, Ocampo found a statistically significant overall positive trend for participants to select the primed response, but no evidence of the impact of novelty. By contrast, we found an overall negative trend for participants to select the primed response in free choice trials, with small statistically significant main effects of both *novelty* and *value* (i.e. whether the answer was "more than" or "less than"). Ocampo did not report value results, but our results indicates some potential default preference for responding in a particular direction (towards "more than") on mobile devices.

For forced-choice trials, Ocampo found a statistically significant main effect of prime agreement (faster RTs for agreement). Instead, we found an interaction effect between novelty and agreement: agreeing responses for repeat primes were slower, compared to agreeing responses for novel primes.

The differences are interesting: our analysis included 101 participants compared to Ocampo's 19. Our results with a larger sample indicate little point in implementing practical applications of subliminal priming, at least of numbers, on smartphones. Ocampo's study provided some evidence that in controlled lab conditions, apparently free choices can be influenced by subliminal novel primes. Our larger sample in a noisier environment with a similar experiment on smartphones found some evidence that free-choices are influenced differently to a small extent by novel and repeat primes, but the rates of selecting the option that matches the prime are close to chance (novel, 50.7%; repeat, 53.6%), the impact of novel is smaller than that of repeat primes, and our measures of model fit are very low. In all, despite some statistically significant differences between the effects of novel and repeat primes, the effects are very small. This may, in part, reflect a general tendency for less-controlled participants to perform tasks faster with less accuracy than lab participants [Findlater et al. 2017], although our visibility tasks results indicate that some pre-existing response behaviours (e.g. to press the right-hand button) may have also influenced the experiment.

In short, our research provides further evidence that subliminal priming is feasible on smartphones but is of limited practical use for NDBCIs. Nevertheless, this experiment shows that semantic processing can have a small limited impact in unbiased stimuli (numbers). It therefore leaves open the possibility that more salient primes may have a larger impact. Our stimuli in Experiment 6.1 (the prime "active") were deliberately biased and intended to place action concepts related to the participants' goals on the Potential Behavioural Stack in our BAF. In the next chapter we therefore re-visit our participant goals from Experiment 6.1 to analyse whether the goal-setting process may have played a part in our lack of results from that study.

Limitations

As with all reaction time data, our data was noisy and some model residuals still indicated some departure from normality. Our R^2 values of model fit indicate that the models were poor estimators of the explained variance. The semi-controlled nature of the experiment meant that participants could be distracted by environmental factors beyond our control, and we had less control over the visual display than in a psychology lab e.g. space between the participant and the screen. The original experiment displayed primes at approximately 10mm high on a 1024x768 monitor, whereas ours displayed primes at a slightly larger size of 20 pts / 50px / 18mm high on our 720x1280 smartphone screens. We used a sans-serif font size 20pts because of evidence that sans-serif fonts and font sizes greater than 18pts are more accessible for dyslexics [Rello et al. 2013; Rello and Baeza-Yates 2013],

and therefore suitable for a more accessible intervention should the technique be shown to be successful.

Summary

Feasibility

We investigated the feasibility of applying subliminal techniques to smartphones. Experiment 6.1 was fairly broad: a week-long pilot in-the-wild into the effect of a repeated text prime on an indirect measure of goal activation. It used priming to try to increase goal accessibility, and two mechanisms to try to increase goal liking and therefore accessibility: the subliminal mere exposure effect (repeatedly exposing participants to the goal prime) [Monahan et al. 2000]; and subliminal affective conditioning via the pairing of a smiley with the goal prime, in line with Murphy & Zajonc [1993]. We found no evidence of impact of the intervention on implicit goal concept activation or on explicit goal commitment measures. Evidence for a decrease in goal commitment scores as a main effect of session *regardless* of intervention suggests that subliminal priming was insufficient to prevent a natural decay of goal commitment over time.

Timings

Experiment 6.2 showed that it is technically possible to show stimuli at the durations similar to those in experiments that have found evidence of subliminal effects, i.e. ~17ms [Dijksterhuis 2004; Hull et al. 2002; Strahan et al. 2002]. Studies 6.2, 6.3 and 6.4 showed only a small number of dropped frames (0.09%, 0.1% and 0.28% respectively), although 6.2 also showed that dropped frames were more prevalent with Wi-Fi enabled (0.32%).

Visibility

Study 6.3 and 6.4 both showed that masking of stimuli on smartphones can partially prevent stimuli from entering conscious perception, in line with Greenwald et al. [1996]. From 6.3, there was no evidence of a stable preference effect for primed stimuli where people could not correctly identify the prime. These findings contrast with Dijksterhuis [2004], but support other HCI studies that could not identify a subliminal effect [Pfleging et al. 2013; Riener and Thaller 2014].

The statistically significant negative impact of the 1xRepetition of text primes on the Preference Task in experiment 6.3 indicates that the effects of subliminal priming are inconsistent across different prime types. This is in line with Winkielman et al.'s findings that "familiar" items may be more

resistant to subliminal affective priming than unfamiliar ones [1997]. Experiment 6.3B showed that maintaining subliminal exposures on smartphones is delicate: even a small change in mask and duration meant that users could 'see' stimuli more clearly. Experiment 6.4 again highlighted the delicacy of designing subliminal primes, showing slightly different effects for novel and repeat primes. We identified a trade-off in selecting the best type of subliminal prime between efficiency metrics of speed and accuracy depending on task type, but only very small effects for either measure.

CONCLUSION

Overall, we conclude that although subliminal priming is technically feasible on smartphones, there is no strong evidence to suggest that smartphones are an appropriate platform for subliminal priming, whether to increase preference or selection of stimuli or to increase behavioural goal activation as part of a behaviour change intervention. We can expect less stable results for both visibility and preference effects in-the-wild. Even where we did identify some effects, our R^2 values were small, and effect sizes were small. In short, subliminal priming is possible but of limited practical use, particularly in the behaviour change domain.

We have found mixed results for low-cognitive load interventions to try to avoid reactance. The best guarantee of avoiding reactance and user irritation is to deliver an intervention that they cannot consciously recall. However, we have shown that it is not technically possible to deliver a subliminal prime without a user being aware that *something* has been shown. This is fortunate from an ethics point of view, but it retains the risk of user irritation. Given that the effects of delivering subliminal priming are small, inconsistent and not expected to be stable in-the-wild, we have found no evidence to suggest that using it as a stand-alone technique is an effective NDBCI.

Our research in Chapter 5 showed some evidence of the shortcomings of both opportunistic training (may still cause irritation) and task-based training (difficult to complete in noisy contexts, and may be insufficient to overcome ingrained behaviour). Therefore, in the next chapter, we move back up the cognitive load continuum back to higher-load interventions, and revisit the potential of goal automation strategies, including Implementation Intentions (Chapter 4). However, instead of relying on potentially disruptive context-aware reminders for Implementation Intentions that risk reactance as in Chapter 4, instead we focus on the *content* of user-set goals to analyse why they might fail, with particular focus on goal automation. Experiment 6.1 suggested that subliminal goal priming was insufficient to prevent a decline in goal commitment over 1 week. The next chapter therefore

analyses how DBCIs might be able to increase goal automaticity without attracting user irritation and reactance by shifting the cognitive load away from intervention time to creation and rehearsal time. The next chapter, Chapter 7, therefore explores how interventions could *combine* multiple NDBCI strategies at varying levels of cognitive load and at different time intervention points with the aim of achieving goal automaticity, i.e. goals are triggered in a low-cognitive-load manner by context cues.

7. QUALITATIVE ANALYSIS OF GOALS

This chapter re-considers the role of multiple NDBCI strategies, including Implementation Intentions (Chapter 4), to generate autonomous goals to achieve behaviour change. It draws on the BAF (Chapter 3) and our study in untracked goal setting (Chapter 6, study 6.1) to discuss strategies for technology to support goal automation via Implementation Intentions by implementing both high- and medium-cognitive load NDBCIs. It:

- uses data from Study 6.1 in a qualitative analysis of 52 freely self-set untracked user goals, and a quantitative analysis of user attitudes;
- generates a Goal Failure Framework which outlines potential sources of failures in technology-supported goal setting; and
- draws on Chapters 3-6 to outline strategies to combine high- and medium-cognitive load Type 1 interventions to counter potential failures by focusing on autonomous goals, shifting the cognitive load of goal activation to goal creation time.

MOTIVATION

The preceding experimental chapters 4-6 have explored various strategies to automate goals, i.e. to embed goal actions in memory in such a way that they are triggered nonconsciously by cues, either already existing in the environment (as in our Implementation Intention and Cognitive Bias Modification chapters 4 and 5) or technology-based (as in our subliminal priming experiments, chapter 6).

Given the lack of statistically significant results in chapters 4 and 5, and the small effects we found for subliminal priming mere exposure effects in Study 6.3 and subliminal semantic priming in Study 6.4, we wanted to further investigate possible sources of goal failure.

First we revisit the goal-setting process we used in Study 4 and 5.1 to identify potential sources of goal failure using a more qualitative approach. Our data was the self-set goals of 52 people who started the 1-week subliminal goal priming study 6.1. With respect to RQ2, ("how can technology best exploit nonconscious opportunities to intervene in a user-friendly way"), as we noted in Chapter 3, theory and evidence suggests that subliminal priming can only be effective where goal actions are sufficiently salient and related to the prime such that they do appear on the Potential Response Stack when exposed to a prime trigger. We were therefore interested to examine what types of goal users

set and to identify why these might fail, i.e. not reach the Potential Response Stack and/or not be enacted.

Secondly, we examine goal attitude measures for both users that completed the study and those that dropped out. Finally, we reconsider the role that Implementation Intentions can have in overcoming potential sources of goal failure so that goal actions appear on the Potential Response Stack.

This chapter addresses 3 sub-questions of RQ2: what physical activity goals do users set?; what are the possible causes of goal failure for goal-supporting DBCIs?; and how might technology address these failures?

INTRODUCTION

Goals are mental representations of desired future states [Hassin et al. 2009]. As shown in Chapters 2 and 3, goal setting is an important construct in much behaviour change theory, and most activity trackers allow people to set goals. However, it is difficult to set *effective* goals, those with appropriate content and sufficient motivation [Ordóñez et al. 2009]. Yet most activity trackers and apps offer default goals [Fritz et al. 2014]. This can be problematic since few users alter default goals: Gouveia et al. found that only one-third of users changed the default [2015], while Tang & Kay found that 67% of users adopted default goal targets [2017a]. Goal mismatch is one factor prompting user disinterest and abandonment [Kim et al. 2017a].

We explored the goals created by all participants who started study 6.1 to examine whether tracker default goals and goal structures are a mismatch with goals that users set in-the-wild. Participants received brief guidance on forming effective goals, could enter their goal in free text, and were explicitly told behaviour would not be tracked. Untracked goals are important because tracking introduces dependence on the tracking device [Renfree et al. 2016], and tracking problems can trigger abandonment and reactance [Clawson et al.]. We then analysed the goals with reference to a Goal Setting Framework, which synthesises why goals fail from Goal Setting Theory and related work.

GOAL SETTING IN PHYSICAL ACTIVITY APPS

Goal setting is a frequent strategy in physical activity apps [Conroy et al. 2014; Middelweerd et al. 2014]. Apps commonly provide a default: Google Fit sets a default of 1 hour's activity a day [Google 2017]; Active 10 sets a default of 10 minutes of active walking per day [Public Health England 2017]; and Fitbit sets a default of 10,000 steps per day [Fitbit 2017].

GOAL SETTING FOR PHYSICAL ACTIVITY IN HCI

Goal setting is a frequent behaviour change strategy in HCI [Munson et al. 2015]. As with apps, much HCI research imposes default goals and/or goal formats. Walsh et al. set a goal of 30 mins walking per day [2016], Gouveira et al. required a daily walking goal with a default of 1km [2015]; and Consolvo et al. asked participants to set weekly goals in a specific format: *<number of sessions><activity type><minimum session duration in minutes>* [2009a].

There is also much research into the use and abandonment of physical activity trackers. Choe et al. [2014] argue the inability of tools to provide goals users want to set drives adoption of other methods. Yang et al. [2015] also suggest that tracker accuracy gaps drive abandonment. This chapter builds on these works, and contrasts with the self-awareness informatics approach, e.g. [Li et al. 2012], to outline a nonconscious goal approach to outsource activation to the user's context to avoid goal and accuracy gaps.

THE GOAL FAILURE FRAMEWORK (GFF)

The GFF is shown in Table 7:1.

Goal component	*Sources of possible failure*
Motivation	Origin Low self-efficacy Attitude
Content	Too abstract Too easy User / System mismatch Conflicts Focus on outcome
Activation	Forgetting Disruption Inattention Reactance High cognitive load
Pursuit	Situational constraints Conflicts
Feedback	Tracking failure Reflection failure Reward mismatch Dependence

Table 7:1 Goal Failure Framework

The GFF analyses why goal-setting interventions might fail by outlining key goal components alongside their sources of possible failure. In addition to Goal Setting Theory components of *motivation*, content and *feedback*, our framework also includes *activation* and *pursuit* components.

Goal motivation

Within Goal Setting Theory, the sources of possible failure in goal motivation are goal origin, low self-efficacy and attitude.

Goal origin

Goals may be freely self-set, assigned by a system or be a collaboration between the user and the system [Locke and Latham 2002]. Both Goal Setting Theory and self-determination theory [Deci and Ryan 2011] suggest that self-set goals provide users with more intrinsic, autonomous motivation to achieve their goals than imposed goals.

Low self efficacy

Self-efficacy is an individual's confidence in their ability to achieve a certain goal, and is a key concept in Social Cognitive Theory [Bandura 1977]. It can be improved by providing training, and persuading people of their abilities. There is evidence that high self-efficacy also affects other motivation sub-components: it impacts on the level of goal difficulty selected, and on goal commitment levels [Locke 1996].

Attitude

Goal *attitude*, including goal importance and affect, are argued to be strong predictors, along with goal progress, of feelings of success by Goal Setting Theory. *Attitude* is similarly assumed to be important in goal pursuit by several theories, including the Theory of Planned Behaviour [Ajzen 1991]. This theory sees intentions, motivations towards goal behaviours, as key predictors of behaviour. Attitude is a predictor of these intentions, alongside subjective norms and an individual's perception of how much control they have over the given behaviour (the latter concept being similar to self-efficacy). A goal towards which a user holds an ambivalent or negative attitude is unlikely to be enacted.

Goal content

Within *goal content*, possible sources of failure according to Goal Setting Theory are goals that are *too abstract* (insufficiently specific) or *too easy* (insufficiently difficult). To this we add the problems of *user-system mismatch*, *conflict* and *focus on outcome*.

User/system mismatch

Several researchers have identified that the inability of tools to provide the goals users want to set drives adoption of other methods [Choe et al. 2014; Kim et al. 2017b]. This mismatch extends to default goals; a substantial proportion of users adopt system goals rather than defining their own. Fritz et al. found users "overwhelmingly" adopted default goals [Fritz et al. 2014], while Gouveia et al. and Tang & Kay both found that around 2/3 of users used default goal targets [Gouveia et al. 2015; Tang and Kay 2017b].

Goal conflict

Although Munson & Consolvo found evidence that users valued multiple goals so an easier goal could be used as a 'fall-back' [2012], multiple goals can interfere with goal pursuit compared with single goals because of *goal conflict*, where multiple behavioural plans match a given situation, which can undermine commitment [Dalton and Spiller 2012] and goal pursuit [Gray et al. 2017].

Focus on outcome

As outlined above, process goals have been found to be more effective than goals that *focus on outcome* [Wilson and Brookfield 2009].

Goal activation

Goal *activation* failures occur where a goal is not pursued because it does not come to mind as a behavioural alternative [Cameron et al. 2017], i.e. never reaches the Potential Response Stack. Activation is captured by the *trigger* concept in the Fogg Behavior Model.

Forgetting

The simplest source of failure is therefore when the individual forgets about the goal. Behaviour change technology often uses a "Just-In-Time" disruption strategy to try and counter the *forget* potential failure in *activation* [Lee et al. 2014; Lee et al. 2017b]. However, there are problems with this strategy: it can lead to *disruption* and *reactance*.

Disruption

Bort-Roig et al.'s meta-review of DBCIs to increase physical activity on smartphones showed that engagement was limited by disruptive prompts and sounds [Bort-Roig et al. 2014]. Other research demonstrates negative impacts of notifications, e.g. disruption and stress [Pielot and Rello 2017;

Westermann et al. 2015], and evidence of inattention: users do not react to them in a just-in-time way [Mehrotra et al. 2016; Pejovic and Musolesi 2014]. Goals on the Potential Response Stack may therefore be downgraded below the Act threshold if users are irritated by prompts, or may never reach it if reminders are not attended to.

Reactance

Reactance is where users respond to a perceived loss of behavioural freedom – e.g. when a system tells them what to do - by acting to restore their freedom – e.g. refusing to comply [Brehm 2009; Ehrenbrink et al. 2016; Roubroeks et al. 2009].

High cognitive load

High cognitive load is an issue over and above forgetting. Dual process theories [Chaiken and Trope 1999; Evans 2008] and limited-resource theory [Muraven and Baumeister 2000] argue that limited cognitive resources mean high load can result in unintended behaviour, not in line with consciously-held goals. We showed in Chapter 3 how competing responses on the Potential Response Stack can result in goal-related behaviour not being enacted.

Goal pursuit

Goal *pursuit* is carrying out the desired behaviour, i.e. the response exceeds the Act threshold and can be enacted. This can be prevented by situational constraints, such as unavailability of sports equipment, or lack of time to complete an exercise class because of a work meeting. Situational constraints as a source of failure feature in many behaviour change theories including COM-B [Michie et al. 2011] and the Theory of Interpersonal Behaviour [Triandis 1977].

Goal feedback

Tracking failures

Tracking failures, where devices cannot accurately capture activities, can frustrate goal behaviour, and even trigger abandonment [Clawson et al.; Yang et al. 2015]. Fritz et al. found some users tailored their goals to their trackers because of limited capture ability, and that trackers failed to adequately support changing activity profiles over time [Fritz et al. 2014].

Reflection failures

A failure of *reflection* involves either the system failing to provide adequate information and/or the user having insufficient cognitive resources to process it [Muraven and Baumeister 2000]. Several studies show users prioritise short-term tracking over longer-term reflection [Gouveia et al. 2015; Rooksby et al. 2014]. Gouveira et al.'s 10-month study of fitness tracker usage found little interest in reflection, with feedback demands dominated by brief glances at current activity [Gouveia et al. 2015].

Reward mismatch

Reward misfit is an issue for activity trackers. Fritz et al. [2014] found users tended to use real-world rewards in addition to system rewards, and that system rewards could skew behaviour towards system not user goals. Munson and Consolvo also found mixed evidence for the efficacy of virtual rewards to motivate behaviour [2012].

Dependence

Even where feedback works perfectly, system *dependence* is problematic if the technology itself becomes part of goal-directed behaviour [Renfree et al. 2016]. Given high turnover in trackers and smartphone ownership, device dependence is not a strategy for long-term success.

The Goal Failures Framework provides a method of identifying possible sources of failure to aid strategic design of DBCIs. Next we outline how we applied the framework to a series of qualitative and quantitative measures from 52 participants from study 6.1.

Study 7.1

Our study addresses two research questions: RQ1: how do users set physical activity goals regardless of tracking?; and RQ2: what are the possible sources of failure when such goals are supported by technology?.

METHOD

PARTICIPANTS

Goals from 52 participants (age: *mean*=27.7, *SD*=7.71; 32 women) were analysed, including 40 completers of the 1-week experiment 6.1[9] (age: *mean*=28.2, *SD*=8.00, 25 women), and 12 drop-outs (age: *mean*=26.0, *SD*=6.64; 7 women). No drop-outs asked for their data to be deleted.

PROCEDURE

As outlined in Chapter 6, participants were recruited with the invite “Do you want to be more active?”. After an online demographics survey, participants were asked to form and commit to an “active goal” in line with Goal Setting Theory. They were told the goal should be clear, specific and somewhat difficult. They were given the example "I will walk for 30 minutes total a day". Participants then received a link to an app that “may prompt you to be more active”. They were specifically told the app did not track location or activity.

MEASURES

As outlined in Chapter 6, all participants completed the HWK sub-scale measure of *goal commitment*, and a set of semantic differentials to explore their explicit attitudes towards *being active* and *being inactive*.

RESULTS

To answer RQ1, what form do user-set physical activity goals take?, we conducted a qualitative analysis of participants’ self-set physical activity goal contents using iterative thematic analysis [Braun and Clarke 2006]. To answer RQ2, what are the possible sources of goal failure when supporting these goals with technology, we interpreted the results using the Goal Failure Framework, and examined quantitative measures of goal commitment and goal attitude.

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[9] *34 of these were included in the analysis in Chapter 6; 6 were not included: 4 had their data excluded, 2 began the study late.*

RQ1: How do users set physical activity goals regardless of tracking?

Table 7:2 shows the results of our thematic analysis.

Goal theme	*Total*	*Completers*	*Dropouts*	*Example*
Specific activity	51	40	11	P9 "I will do sit ups every day for 30 minutes"
Day-based	43	35	8	P24 "I will do two 15 mins walks a day"
Trackable	34	26	8	P44 "I will walk over 10,000 steps every day"
Duration	30	25	5	P4 "I will walk for 90 minutes each day"
Default	17	16	1	P23 "I will walk for 30 minutes each day"
Completion	15	11	4	P16 "I will complete my push up routine every day"
Week-based	10	5	5	P21 "Walk for 20 minutes for 3 days in the week"
Step-based	5	4	1	P36 "I will walk or run 20000 steps a day"
Flexible	5	3	2	P37 "To walk or run for 30 minutes each day"
Multiple sessions	5	2	3	P3 "I will do 30 press ups a day. 15 morning and evening"
Specific sessions	4	3	1	P43 "Go to two spinning classes (>45 min each) per week"
Context-aware	4	1	3	P9 "I will leave home at 7.20am Monday-Friday"
Chaining	3	2	1	P31 "I will go and come back from the gym running"
Additional	3	2	1	P39 "Walk for 30 minutes a day (outside of commuting)"
Google Fit[+]	25	21	4	P47 "I will walk for 60 minutes total a day"
Google Fit / Fitbit default	9	7	2	P11 "I will walk for 60 minutes a day"

[+] goal activity that can be automatically tracked by Google Fit

Table 7:2 Goal themes emerging from 52 freely-set physical activity goals

Two key high-level theme groups were activities and timeframes.

ACTIVITIES

Table 7:3 shows the main physical activities our participants mentioned in their goals.

Activity	*Mentions*
Walk	30
Run	8
Vigorous exercise	7
Push-ups; sit-ups	5
Cycle	2

Table 7:3 Top 5 activities mentioned

Walking was by far the most popular activity, included in 30 goals (58%). The results also show some level of abstraction: 7 goals mentioned "vigorous exercise" or similar (e.g. high-intensity exercise) (13%), which indicates a lack of specificity according to Goal Setting Theory. We grouped push-ups and sit-ups together as similar strength exercises, mentioned in 5 goals (10%).

TIMEFRAMES

Only 2 users did not specify a timeframe for their goals, and the timeframe was overwhelmingly **day-based**: 43 participants (83%) used per-day goals. In line with previous research, most durations were defined as totals rather than minimums [Mentis et al. 2017]. One participant defined both a day-based and a week-based goal. Only 6 participants (12%) specified minimum or at least durations, e.g. P50 "*High intensity exercise 30 minutes at least a day*".

30 participants (58%) specified a **duration-based goal**, e.g. P38 "*I will walk for over an hour every day this week*". The overall mean duration specified was 39.5 minutes (*SD* =21.1), with completers tending to specify slightly longer durations on average (*mean*=41.0, *SD*=21.0) than dropouts (*mean*=33.3, *SD*=22.7). 15 participants (29%) specified a **completion goal** e.g. P31 "*I will reach 8000 steps every day*".

RQ2: What are the possible sources of goal failure in our set of goals?

This section outlines how we analysed our results for potential goal failures using the Goal Failure Framework. We analysed the goal components of the framework in turn: motivation, content, activation, pursuit and feedback.

GOAL MOTIVATION

The Goal Failure Framework identifies low self-efficacy, origin and attitude as possible sources of goal failure within the motivation component.

ORIGIN

Our goals were all explicitly self-set so according to the Goal Failure Framework, there are no potential goal failure issues from system-set goals.

SELF-EFFICACY

We did not explicitly test participants' self-efficacy. Requiring participants to self-set specific, concrete, challenging goals implicitly requires them to select goals that they realistically think they can achieve. However, it is difficult to establish the appropriate relationship between task difficulty and self-efficacy.

ATTITUDE

Our first attitude measure of participants' goals themselves was the HWK goal commitment subscale measure. Table 7:4 shows the descriptive statistics for the HWK for both completers (n=40) and dropouts (n=12).

Group	*Mean*	*SD*	*Lower 95%CI*	*Upper 95%CI*
Completed	4.27	0.46	4.12	4.41
Dropouts	4.08	0.50	3.76	4.40

Table 7:4 HWK subscale descriptive statistics

Internal consistency was good (6 items, α=.72), and the mean scores in each group were tested for normality (all $p > .05$). Welch t-tests showed no evidence of a statistically significant difference in HWKs between participants that completed the experiment and those that did not $t(16.8)=1.13$, $p=.28$, mean difference=0.14, 95%CI[-0.53, 0.16], Cohen's $d=0.38$). There was also no evidence of a statistically significant difference between HWKs of participants that adopted default goals or not $t(30.46) = 0.60$, $p=.55$, mean difference = 0.09, 95%CI[-0.21, 0.38], Cohen's $d=0.18$.

These results are somewhat counter to the contention of the Goal Setting Theory that self-set goals (i.e. not adopting the default) should be associated with higher levels of goal commitment, and an implicit assumption that higher levels of goal commitment would be associated with experiment completion. However, we also note that absence of evidence of an effect is not evidence for the absence of that effect. For ethical reasons, we were also unable to gather data on *why* participants dropped out; it may have been for reasons unrelated to goal commitment. Further research is therefore required to disambiguate these null results.

Our second measure was of explicit attitudes towards being active or inactive more generally. Data for 2 participants for explicit active and inactive attitudes was lost, leaving 50 participants (39 completers; 11 dropouts). Scores for active and inactive attitudes were tested for normality across the completion groups (all $p > .05$).

Table 7:5 shows the descriptive statistics for the attitude measures.

Attitude	*Group*	*Mean*	*SD*	*Lower 95%CI*	*Upper 95%CI*
Active	Completed	4.22	0.40	4.09	4.35
	Dropouts	4.44	0.25	4.28	4.61
Inactive	Completed	2.11	0.60	1.91	2.30
	Dropouts	2.06	0.71	1.59	2.55

Table 7:5 Descriptive statistics for explicit attitude measures

Internal consistency was acceptable for both attitude measures (8 items, active: α =.64, inactive: α =.77). Attitude scores towards being active for completers (mean=4.22) and dropouts (mean=4.44) had a statistically significant difference according to a Welch's *t*-test, $t(26.7)=2.23$, $p=.03$, mean difference =0.22 , 95%CI[0.02, 0.42], Cohen's $d=0.66$. Note that we did not adjust the *p* values using a Bonferroni correction to reflect the fact that we have analysed parts of this data before in previous chapters. Slightly counterintuitively, this indicates that dropouts tended to start out with more positive attitudes towards being active than those who completed the experiment. Attitude scores towards being inactive did not have a statistically significant difference between completion groups according to a Welch's *t*-test, $t(14.18)= 0.16$, $p=.88$, mean difference = 0.04, 95%CI[-0.54, 0.47], Cohen's $d= 0.06$.

We identified a statistically significant weak negative correlation between active and inactive means, $r(46)=-0.35$, $p=.01$. This means that although, as expected, there is a negative relationship between attitudes towards being active and being inactive, only a small proportion (12%) of the variation in the active attitude measure can be explained by our inactive attitude measure. For designers of systems supporting physical activity goals, gathering both measures should therefore be considered, since one measure cannot be assumed from the other.

GOAL CONTENT

The Goal Failure Framework suggests that within goal content, potential sources of failure are: too abstract, too easy, user/system mismatch, conflicts and focus on outcome.

TOO ABSTRACT

51 participants (98%) mentioned **particular activities** in their goals, as shown in Table 7:3. However, as we noted above, some were abstract (e.g. P50 "*High intensity exercise 30 minutes at least a day*") which may indicate problems in goal attainment according to Goal Setting Theory, since it requires goals to be specific.

TOO EASY

As noted above, there is some tension between self-efficacy and goal difficulty. Participants were requested to set moderately difficult goals, but in the absence of data over prior participant behaviour, it is difficult to establish the extent to which they complied. One strategy to overcome the "too easy" problem is the imposition of a step goal 10% above participants' baseline [2014] or setting goals based on the participant's existing routine [Cabrita et al. 2014]. However, this strategy may in turn cause goal failures because it is a system-set rather than user-set goal.

USER/SYSTEM MISMATCH

17 participants (33%) set goals in line with the **default goal** given in the goal setting instructions, "I will walk for 30 minutes total a day". 5 participants directly adopted the default, while 12 participants set variations including different durations or using the default as a minimum. 9 participants (17%) set goals the same as the Google Fit or Fitbit defaults outlined above.

CONFLICTS

We only asked participants to set one physical activity goal for the purposes of our experiment. Nevertheless, 5 (10%) mentioned multiple activities (e.g. P36 "*walk or run"*), while the same number mentioned splitting their activity into multiple sessions. We also did not ask participants about other concurrent behavioural goals that may conflict. We should therefore consider goal conflicts as a possible issue.

FOCUS ON OUTCOME

We found no cause for concern in this category: all participants set **process goals** (e.g. perform a given exercise for a specific amount of time) rather than **outcome goals** (e.g. lose a certain amount of weight).

GOAL ACTIVATION

The Goal Failure Framework proposes that the following are potential sources of failure within *activation:* forgetting, disruption, inattention, reactance and high cognitive load.

FORGETTING

Very few participants formed goals that might be triggered by contextual features, including pre-existing behaviours, risking potential forgetting since they are not reminded of their goals by the environment or other behaviours. Only 4 participants (8%) formed **context-aware goals**, which

mentioned specific locations and/or times and locations in which to perform the goal behaviour, e.g. P9 "*I will leave home at 7.20am Monday- Friday to get to university*".

Even fewer participants (3, 6%) formed **chaining goals** linked to pre-existing behaviour, e.g. P31 "*I will go and come back from the gym running*". 3 (6%) defined **additional goals**, activity in addition to existing behaviour (e.g. P39 "*walk for 30 minutes a day (outside of commuting to lectures)*".

DISRUPTION, INATTENTION, HIGH COGNITIVE LOAD

Our experiment delivered goal reminders at the point at which participants unlocked their smartphones. This is a disruptive strategy, which risks inattention, particularly if participants were under situations of high cognitive load e.g. if they had another task in mind for which they were unlocking their smartphone.

REACTANCE

We avoided using a direct behavioural command in our goal reminder to try to minimise reactance. Nevertheless, given that the purpose of our intervention was to remind participants of their goals, it risked triggering reactance.

GOAL PURSUIT

We did not directly mitigate against goal pursuit issues that may occur through situational constraints. However, the experiment instructions asking participants to set goals that they could commit to achieving over one week implicitly requires them to consider at least short-term constraints within their goal setting procedure.

GOAL FEEDBACK

The Goal Failure Framework proposes that sources of failure within goal feedback are tracking failure, reflection failure, reward mismatch and dependence.

TRACKING

The majority of participants (34, 65%) set goals that *could* be **tracked** – e.g. minimum walking durations, but only 5 (10%) set goals that *require* tracking, i.e. step-counts, which without tracking are difficult to self-estimate.

We assessed whether each goal was trackable within a particular fitness app, **Google Fit** [Google 2017], without the user having to enter their own information. 27 (52%) of goals were not trackable.

Some of the failures were due to different timeframes: for example "*I will run 3 times a week for 30 minutes each*" (P13). Although Google Fit has a weekly view, it shows weekly totals, not per-day session within a week. Other failures were due to specific exercises (e.g. push-ups are not easily trackable) or attending fitness classes (e.g. yoga).

REFLECTION, REWARDS

Neither of these sub-components were explicitly included in our experiment design, so they are not a direct possible source of failure. Nevertheless, further research is required to determine whether their absence is in itself a possible source of failure.

DEPENDENCE

Our experiment did provide goal reminders to participants. Therefore, dependence is a potential issue in achieving longer-term goal behaviour if participants required the reminders in order to perform their goal behaviour, rather than learning to perform the behaviour regardless of prompts from technology. Once the prompts stop, so does the goal behaviour.

Table 7:6 summarises the possible failures in goal-related behaviour we have identified within our set of goals by analysing them using the Goal Failure Framework.

Goal component	*Possible failure identified*
Motivation	Attitude
Content	Too abstract User / System mismatch Conflicts
Activation	Disruption Inattention Reactance High cognitive load
Pursuit	Situational constraints Conflicts
Feedback	Tracking failure Dependence

Table 7:6 Sources of possible failure identified from our participants' goals

Discussion

Our aim was to establish what physical activity goals are freely set in-the-wild, what their potential sources of failure are when supported via technology, and to identify strategic design options to overcome these failures.

Our participants tended to set process, day-based physical activity goals that feature walking. Our results indicate that apps need to support considerable flexibility in goal setting. Participants set more duration-based goals than step-based goals, but both should be supported. Likewise with durations: users employed both day- and week-based goals.

The re-use of our example goal amongst the participants supports research that participants tend to accept default goals on activity trackers [Fritz et al. 2014; Tang and Kay 2017b]. Careful design of the default option is therefore critical. Default goals may also have driven 17% of participants to select goals that feature as default in Google Fit and Fitbit. Thus we have established evidence of some overlap between goals set in–the-wild and app-determined goals.

We found evidence that users do not tend to set goals that can be activated autonomously: few participants set context-aware or chained goals. We also found evidence that users tend to set goals that cannot easily be tracked to provide adequate goal feedback. Although many goals had trackable features, we identified mismatches in goal timeframes with Google Fit (users defined *x days per week* goals) and in activity type (e.g. push-ups). According to Goal Setting Theory, untracked goals are less effective, yet manual tracking requires scarce cognitive resources.

In terms of goal motivation, we found some evidence that participants who dropped out started with a more positive attitude towards being active than completers, although the effect was not stable across our two different measures of goal attitude. This may indicate some overconfidence effect that warrants further research. However, possible overconfidence is not shown elsewhere since completers tended to specify longer durations for physical activity than dropouts, and the difference in attitudes between completers and dropouts is not significant at a Bonferroni-corrected p value.

Our attitude score results indicate only a weak negative relationship between attitudes towards “being active” and “being inactive”. These measures cannot therefore be considered the converse of each other, and system designers should consider gathering both measures. We also found that measuring attitudes towards activity and inactivity using simple semantic differentials had acceptable internal consistency.

Solutions

Our analysis shows multiple potential sources of goal failure. To address these, we return to the concept of Implementation Intentions as discussed in Chapters 3 and 4. Using these, NDBCIs can target the sources of potential goal failure as shown in Table 7:7.

Goal component	*Implementation Intention NDBCI mechanism to counter potential goal failure*
Motivation	No need to maintain it and/or use complementary motivational interventions.
Content	Guide sufficiently specific goals that avoid conflicts.
Activation	Avoid disruption, inattention, reactance and high cognitive load issues by shifting activation to contextual cues.
Pursuit	Guide users to identify situational constraints;. Identify and avoid cue conflicts
Feedback	*Avoid need for tracking and dependence*

Table 7:7 Implementation Intention mechanisms to address goal failures

How, then might Implementation Intention NDBCIs address these potential failures?

GOAL MOTIVATION

Implementation Intention NDBCIs can avoid having to target the *goal motivation* concept: a sufficiently embedded Implementation Intention does not require ongoing goal motivation to activate. There is evidence that goal motivation does not increase Implementation Intention interventions [Sheeran et al. 2005b], which implies that the differences in goal motivation scores we observed in our participants and dropouts are not important. However, there is also evidence that NDBCIs focusing on Implementation Intentions can be complemented by DBCIs targeting Type 2 concepts. Milne et al. [2002] found that a motivational Type 2 intervention aimed at increasing participants' self-efficacy around exercise combined with an Implementation intentions intervention increased compliance to 91% compared to motivational-only compliance rates of 39% and control compliance rates of only 29%.

GOAL CONTENT

Implementation Intention NDBCIs should target the *goal content* component by guiding and supporting create and commit to an Implementation Intention at the outset to fulfil their goal in each stable context they encounter. Our results show that users wish to set a wide range of goals. Interventions should identify and suggest salient *if* triggers within each stable context, and support the user to create appropriately difficult, specific accompanying *then* goal behaviours. Give our results, interventions should avoid not only restricting *thens to* particular types of goal, but also avoid

defaults. Implementation intentions effectively 'train' a user to respond to contextual triggers as an alternative to having to perform complex anticipatory calculations in order to determine when and how to provide just-in-time goal reminders [Pejovic and Musolesi 2015]. Lightweight cognitive bias modification techniques may also be used (see Chapters 3 and 5) to increase the salience of the selected contextual triggers, again enhancing the likelihood that the related goal action will appear on the Potential Behaviour Stack.

Interventions should also employ chaining, where a desired behaviour is linked to a pre-existing behaviour that has already become somewhat routine or automatic. If successfully linked, then performing the existing behaviour should trigger the new behaviour without the need for additional reminders or prompts [Judah et al. 2012].

GOAL ACTIVATION

Implementation Intention NDBCIs explicitly target the *goal activation* component to achieve Type 1 nonconscious, autonomous activation without being affected by inattention, reactance or high cognitive load. As we have argued above and in Chapters 3 and 4, for goal automaticity, users need to establish goals that are brought to mind by salient contextual cues [Aarts and Dijksterhuis 2000; Gardner et al. 2012b] instead of by disruptive Just-In-Time reminders that may be ignored, missed, or interpreted adversely. Chapter 4 highlighted possible irritation and reactance issues with context-aware proximity triggers as reminders to support them. An alternative is to shift cognitive load away from disruptive reminders at activation time to goal creation time, i.e. focusing on *goal content* as outlined above.

Yet *goal content* support may not overcome all potential goal activation failure since goal accessibility decays over time [Tobias 2009]. Rehearsal may enhance goal achievement by improving cognitive saliency and therefore accessibility of Implementation Intentions [Knäuper et al. 2011; Veling et al. 2014]. Therefore, interventions should also provide users with multiple opportunities for Implementation Intention rehearsal to deepen their trigger-behaviour associations. Stawarz et al. suggest that reminding people *before* the intended goal-enactment time , i.e. to remind them *of* their intention rather than at the intended moment of action, can encourage people to remember the intention without technology dependency [Stawarz et al. 2015]. Shifting the cognitive load of goal activation from high-load disruption to medium-cognitive load training or rehearsal phases in this way has the advantage of not disrupting users at an intended goal-enactment time.

GOAL PURSUIT

Implementation Intention NDBCIs should address situational constraints that might hamper goal pursuit at goal content (creation) time: they should explicitly ask users to consider previous failures due to situational constraints and develop Implementation Intentions to avoid or overcome them. Such NDBCIs also need to guard against cue conflicts. Goal automating methods are not without risk because the higher the number of cognitive connections a goal has, the more likely it is to be triggered, but the higher the likelihood of goal conflict [Austin and Vancouver 1996], and see Table 3.1. Interventions should therefore (a) promote Implementation Intentions with the smallest number of salient cues as if triggers; and (b) monitor possible conflicts and advise users of them.

GOAL FEEDBACK

Although several researchers have suggested the use of context to support feedback for physical activity goals, e.g. [Gouveia et al. 2015; Lee et al. 2014], again the focus tends to be on a self-awareness strategy to aid post-behaviour recall and planning, rather than a strategy to support goal activation itself. Context is also used as a strategy to target *forgetting*, often using a disruptive alert. However, Ding et al. found such context-aware alerts still frustrated users, risking reactance [Ding et al. 2016]. Implementation Intention NDBCIs can instead be seen as a feed-forward loop that can drive goal enactment regardless of feeback [Gärling and Fujii 2009; Vermeulen et al. 2013].

EXAMPLE

Taking the example goal of "*I will do two 15 mins walks a day*" (P24), systems should support the user to identify appropriate triggers and specific behaviours for each walk, e.g. "*If* I have finished my breakfast, *then* I will go for a 15 minute walk to location Z"; "*If* I have picked my kid up from the school, *then* we will walk home via the park".

These Implementation Intentions also incorporate the notion of chaining – pre-existing entrenched behaviours (eating breakfast; doing the school run) that can be co-opted as triggers from the new behavioural goals. A system should support the user to rehearse these Implementation Intentions, both by straight mental rehearsal, and by the use of user photos of the relevant context to further deepen the trigger-behaviour associations. Interventions should also design defensively against conflicts by tracking multiple Implementation Intentions and warning of possible conflicts between multiple triggers and multiple behavioural goals.

Limitations

Due to ethics considerations, we did not contact our dropouts to ask *why* they did not continue with the experiment. The dropout group was also relatively small (n=12). Our timeframes analysis is limited since participants were directed to form a goal for a week-long experiment. We did not ask participants about concurrent use of goal-tracking technology, which may have primed their selection of an activity goal. There is a limit to the extent to which our participants' goals can be considered to be freely set regardless of tracking: they were still participating in an experiment on their smartphones, which may have implicitly primed goals with some expectations of tracking.

Goal-setting is not a panacea to bridge intention-behaviour gaps due to possible side-effects [Ordóñez et al. 2009]. Likewise, evidence that self-set goals are more effective than alternatives is not equivocal [Shilts et al. 2004], and evidence on the relative efficacy of goals set collaboratively between users and their technology is sparse.

Summary

We argue that strategic deployment of NDBCI techniques that require varied levels of cognitive resources may be the most promising avenues of future research. Shifting high-load collaborative goal-setting within Implementation Intentions to the start of an intervention, together with medium-cognitive-load NDBCIs such as rehearsal in later stages, may best support users to generate autonomous goals that can alleviate multiple aspects of goal failure. Goal setting stages could also be augmented with trigger identification, cognitive bias modification in favour of the triggers, chaining advice and warnings of possible trigger clashes where possible. If the high- and medium- load strategies are deployed correctly, then goals should be triggered autonomously by the environment in a low-load manner.

8. GENERAL DISCUSSION

This chapter:

- summarises the findings of the previous chapters
- discusses the limitations of the BAF and our research
- synthesises the lessons learned in theory, users and technology to guide future research
- presents design guidelines for NDBCIs
- outlines our contributions to research.

FINDINGS SUMMARY

What, then, have we discovered about targeting automatic processes to achieve behaviour change? The central research questions for this thesis were: (1) to identify nonconscious influences on behaviour; and (2) identify how best to use technology to intervene to alter them.

Question 1 was addressed by Chapters 2 and 3. Chapter 2 examined the theoretical underpinnings of nonconscious interventions, arguing that a lack of focus on nonconscious influences has contributed to intervention failure. Chapter 3 outlined a theory-based framework incorporating both conscious and nonconscious influences on behaviour, the Behaviour Alteration Framework. This identified multiple opportunities to target nonconscious processes at the Filter, Prepare and Act stages of behavioural preparation.

We next moved to address Question 2: how best to exploit these opportunities. Chapter 3 incorporated evidence from related research into the intervention points of the BAF. Chapter 4 took the strategy of Implementation Intentions and explored how context-aware technology could be used to support them. We ran a pilot and a qualitative survey to understand what sorts of Implementation Intentions people want to form. We found users needed more support than anticipated to form automatable Implementation Intentions, with intelligibility issues in our app. Our survey identified potential issues with just-in-time Implementation Intention interventions, including reactance and simple ignoring.

Chapter 5 addressed these user concerns by shifting focus away from just-in-time interruptions to training-based interventions. It investigated the strategy of Cognitive Bias Modification on two different platforms – smartphones and Tabletops – in two different domains – healthy eating and

smartphone addiction. Experiment 5.1 investigated whether opportunistic accept and reject training of food images on smartphones alters specific and general measures of healthy and unhealthy food liking. We found little evidence of any statistically significant impacts of the intervention. Follow-up survey Study 5.2 found evidence that users were concerned about irritation with opportunistic training and smartphone over-use; and they did not wish to use their smartphones to redress the latter. We therefore designed Experiment 5.3 to explore a task-based CBM to counter smartphone over-use delivered on a Tabletop. It explored whether smartphone approach/avoid bias was related to smartphone addiction scale scores, and whether the bias was alterable via training. Results showed no evidence of an effect of the training, and indicated 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. For both Experiment 5.1 and 5.3, there was the problem of determining whether nonconscious or conscious processes were activated by a visible training paradigm.

We addressed this problem in Chapter 6 by focusing on subliminal priming experiments. Conscious perception of stimuli was masked so effects could be attributed to nonconscious processes. Experiment 6.1 explored whether nonconscious goal priming on smartphones at unlock time alters implicit and explicit measures of goal activation. We found no evidence for a change in implicit measures, and evidence that self-report measures of goal commitment decreased over a week for all participants. To disambiguate these results, we ran a series of follow-up experiments. Experiment 6.2 established that it is technically possible to deliver primes on smartphones at rates that have previously been used in subliminal experiments. Experiments 6.3 and 6.4 used semi-controlled conditions to examine the immediate impact of subliminal priming. Experiment 6.3 explored the subliminal mere exposure effect: whether participants would tend to prefer stimuli (polygons, photos, text) they had just been primed with even when they could not consciously recall them. The results showed difficulty in concealing stimuli, and even where participants could not identify them, contradictory results in terms of preference across different stimuli types. Follow-up experiment 6.3B confirmed the fragility of the masking effect, with our small changes to presenting polygon stimuli rendering them more visible. Experiment 6.4 focused on semantic subliminal priming effects on smartphones. It explored whether masked congruent number primes would decrease reaction times and tendency to select the correct answer; whether free choices could be affected by subliminal primes; and whether novel primes (not used as targets) would have a different effect to repeat primes, indicating that semantic processing occurs with subliminal primes. We found no evidence that participants could detect the primes, but mixed effects for novel and repeat primes. The

experiment showed evidence that subliminal semantic processing of numbers does occur on smartphones, and thus there is some potential for nonconscious goal activation, but the results are of limited practical use because they are not consistent across conditions and the size of the effects was small.

Overall, we have established user scepticism over just-in-time interruption strategies, little evidence of effects with CBM-Ap training, and mixed evidence of subliminal effects on smartphones with very small effect sizes. In short, although from a theoretical and empirical viewpoint we established a solid foundation for taking nonconscious processes into account in DBCIs, we did not find equivocal evidence for the impact of NDBCIs that use single techniques to target Type 1 processes. Instead, we found several limitations in applying techniques from psychology labs into more realistic in-the-wild and semi-controlled environments.

Referring to the continuum of cognitive load imposed by an intervention (Table 1:1), we therefore outlined in Chapter 7 how NDBCIs might deploy multiple strategies, by targeting high-cognitive-load conscious processes at goal creation time, and then use medium-load rehearsal in early intervention stages, rather than use just-in-time or opportunistic training type interventions to establish automatic Type 1 goals. Chapter 7 analysed a set of 1-week activity goals, partly arising from Experiment 6.1, drawing on the lessons learned from Chapters 4,5 and 6, and theory in Chapters 2 and 3, to outline a Goal Failure Framework and establish how interventions might address sources of goal failure to automate goals by shifting cognitive load away from goal activation to goal creation and rehearsal time.

We have shown that at the high-cognitive-load end (disruptive context-aware Implementation Intention reminders) and with medium-load opportunistic training, there is a risk of annoyance and reactance, while at the low-load end where these risks are minimised, effects do not appear stable enough to deliver a reliable change. To address this trade-off, we argued in Chapter 7 that a promising avenue of future research is combining different-load strategies by focusing on high cognitive load at pre-behaviour training with medium-load rehearsal in order to establish Implementation Intentions that automate goals to achieve low-load interventions that are triggered by the user's context. This transfers goal activation to salient triggers in the environment, rather than creating a dependency on the technology and risk alienating users.

Building behaviour-change systems requires an understanding of both behavioural psychology and interaction design [Dix 2016]. We have used behavioural psychology to build the BAF, and explored

various interaction design options within the framework. We argue that understanding nonconscious processes is central to explaining why behaviour change is difficult and why conscious behaviour change interventions tend to fail. Yet a research gap remains in determining how best to target those nonconscious processes. Chapter 7 argues that a possible way forward is to time-shift cognitive load to goal setting and rehearsal time, rather than disrupting users at goal behaviour time.

Synthesis: Theory, Users and Technology

Our introduction and Chapters 2 and 3 identified issues in theory, users and technology as barriers to developing effective DBCIs. This thesis has provided a theory-based framework for (N)DBCIs, and focused on alternatives to 'just-in-time' context-aware interventions to address issues with users and technology to such interventions.

Theory

We have established a theoretical gap in common behaviour change theories to address the influence of Type 1 processes. The BAF addresses the theoretical gap in understanding why people sometimes act against their conscious intentions and goals. We expanded on the possible sources of goal failure in Chapter 7. The frameworks (the Behaviour Alteration Framework and the Goal Failure Framework) require further refinement from empirical evidence.

Users

Domains of concern

Survey 4.2 showed that reported domains of behaviour change concern are health (increase physical activity, eat more healthily, drinking more water) and productivity (avoiding procrastination). Survey 5.2 also showed concerns around healthy eating, physical exercise and problematic technology use. Within the physical activity domain, study 7.1 showed that participants primarily focused on walking, with day-based and duration goals being most frequently selected. Concerns over problematic technology use were also found in study 5.3: 43% of participants reported having a "maladaptive dependency or addiction" over their smartphone usage. A key additional theme that emerged from study 5.2 was user-reported problems in controlling automatic behaviours.

Reactance

We found spontaneous mentions of the possibility of reactance and annoyance towards DBCIs in our qualitative elicitation surveys, 4.2 and 5.2. However, we found no evidence of reactance issues from our subliminal priming 1-week intervention, study 6.1.

Survey 4.2 results also showed a continuum of attitudes towards disruption, from users requesting interrupting alarms to users requesting unobtrusive notifications. This highlights the importance of providing tailoring of disruptive interventions.

Ethics

The BAF shows the potential impact of Type 1 processes on attitudes and behaviour. This impact has not been ignored by the advertising industry. There is evidence that advertisers are increasingly using NDBCI behaviour change techniques to increase consumption of their products, yet academic analysis of the impact of nonconscious advertising via new technology platforms lags behind their popularity [Nicholls 2012].

Three broad developments indicate advertisers are moving towards using "dark patterns" [Brignull 2011; Greenberg et al. 2014] that exploit psychology to influence people beyond their intentions: (i) increased use of technology-driven behavioural targeting, generated from both explicit user-shared information and implicit user information derived from behaviour such as browsing activity [Alt et al. 2009]; (ii) increased use of neuroscience-based physiological monitoring to fine-tune nonconscious responses to adverts [Kennedy and Northover 2016; Khushaba et al. 2013]; and (iii) a movement towards 'native' ads, adverts integrated into social network content so they are difficult to distinguish from content [Lee et al. 2016; Maréchal 2016]. These trends combine to create an asymmetry of information between advertisers and their targets. Advertisers know who has been watching their adverts and when, with what emotional affect and behavioural effect, with what interaction and in what context, while users are unable to consciously recall adverts. Couldry & Turrow [2014] argue that this asymmetry threatens democracy itself by eliminating collective experience: advertisers will be able to show different versions of reality to different audiences. The asymmetry has prompted calls for research into how technology might enable people to protect themselves against advertisers who seek to influence consumers' choices beyond their conscious control [Bargh 2002; Hassine 2014; Sunstein 2016]. The BAF provides a framework within which to carry out such research.

TECHNOLOGY

CONTEXT DETECTION

The BAF outlines the critical impact of context on behaviour. Yet, as we found in study 4.1, smartphones without proprietary software or hardware can only support relatively limited context detection. Study 4.1 also indicated possible intelligibility issues with rich context-detection features that require further research. Survey 4.2 investigated the feasibility of proximity beacons to support Implementation Intentions, with respondents identifying a rich set of possible locations for them. The approach needs experimental testing.

There are two key strands of future research into the use of context-aware pervasive technology to support highly individualised BAF-based interventions. Firstly, to use technology to find out which features of BAF are active at different points for different behaviours for a given individual; secondly to exploit this knowledge in DBCIs that allow that individual to pick-and-mix their own interventions.

TRIGGER HUNTERS

Type 1 context-response associations are not easily available to introspection, but pervasive technology could potentially discover which cues act as triggers for particular unwanted responses. This would address the challenge of fluid causal influences affecting both Type 1 and Type 2 systems in-the-wild [Michie et al. 2013b]. Once discovered, people can avoid, approach and/or retrain their trigger cues accordingly. Technology with richer contextual awareness, including mood-detection, could identify both existing cues that trigger unwanted behaviour and candidate salient cues to be associated with wanted behaviours. Advances in context-cue detection and behaviour detection, perhaps driven by machine learning techniques [Banovic et al. 2017], will broaden our understanding of what sorts of cues can act as response triggers for different types of behaviours.

SELF PICK-AND-MIX

Future research should focus on enabling individuals to vary interventions according to preferences, personality traits and different digital devices [Lee et al. 2017a; Orji et al. 2017; Meinlschmidt et al. 2016]. For example, interventions could allow people to use their own images of real-life problematic cues in CBM-Attention interventions. We foresee a crucial role for such flexible, tailored DBCIs to help solve the problem of fundamental variability in human behaviours, motivations and contexts [Rogers 2006]. From our analysis in Chapter 7, we also argue that this tailoring should extend to level of conscious attention available. This requires further research into reliable detection of what

cognitive resources are available. The pick-and-mix DBCI trend may also help avoid reactance if users feel more in control of their technology.

Smartphone unlock usage

Two studies (5.1, 6.1) explored using opportunistic interventions tied to smartphone unlocks as an intervention strategy. We found that users unlocked their phones around 50 times per day (5.1 mean = 51; 6.1 mean = 49), slightly higher than previous research (Harbach et al. 40 unlocks/day [2016]; Hintze et al. 25 unlocks/day [2014]). We found high variance in usage in line with previous research e.g. [Truong et al. 2014]: study 5.1 showed that one participant took 2 days to complete the intervention, while another took 11 days; and study 6.1 showed that the standard deviation of smartphone unlocks was relatively high compared to the mean. Therefore, although tying interventions to smartphone unlocks is a good candidate for delivering multiple interventions per day, consistent usage across users cannot be assumed.

As noted above, we also found evidence that people are concerned about technology overuse.

Suitability of smartphones for subliminal priming

Our analysis of the suitability of smartphones as a platform for subliminal priming showed few issues with dropped frames on our experiment phones with Wi-Fi disabled, but enabling Wi-Fi (a proxy for higher load) increased the dropped frames. Where a stimulus is only shown for one frame, a dropped frame is clearly an issue. Repeating the timing results on a broader range of phones in-the-wild would be an important future step to gauge the broad technical applicability of the strategy. Regardless of the technical restrictions, we also found only mixed evidence to support the impact of subliminal priming.

Integrating Theory, Users and Technology

In Chapter 7, we drew on our research into theory, users and technology in previous chapters to synthesise a Goal Failure Framework that explored potential reasons for goal failure where technology supports users to create and pursue goals. We showed multiple potential sources of goal failure, including goal activation, where sparse cognitive resources mean users do not recall the goal activity. Further, where interventions try to achieve activation through reminders, even where they managed to overcome issues with context detection to determine the correct reminder time, they still risk goal failure through user inattention and/or reactance. We therefore argue that a key strand of future research for interventions should be to focus shifting cognitively-intensive interventions to

goal creation time to make Type 1 goal activation more likely in the future. Interventions should support users to form automatable goals that tie behaviour to context cues by: identifying appropriately specific and difficult goals with simplified behaviour and cue triggers; encouraging chaining where appropriate; avoiding ironic goals; providing opportunities for rehearsal and identifying cue clashes.

LIMITATIONS

This section summarises the limitations of our experiments.

The main limitation of our experiments is that, in common with many HCI experiments, they were run in the short term and did not use a direct measure of behaviour. The rationale for this was that we were investigating elements of the BAF in NDBCIs. However, this has resulted in an attenuated experimental process: we have assumed that various measures of implicit activation (e.g. emotional Stroop measure of goal activation; reaction times; SRHI) are linked to behaviour, and have measured on the former. This is partly due to the failures of context-aware technology to adequately capture actual behaviour: in a longer-term pilot measuring daily steps[10], we were unable to distinguish between days where participants did not carry their smartphone and days on which they did nothing.

There is ongoing debate about the use of self-report measures to indicate implicit activation and related behaviour [Sniehotta and Presseau 2012; Nilsen et al. 2012]. Self-report indicates an individual's view of what processes are impacting on them, but this is unlikely to be the full picture since the content of Type 1 processes are unavailable to introspection [Hagger et al. 2015]. Self-report should therefore be used with caution. For example, as we showed in Chapter 7, the converse of a particular concept (e.g. 'activity' vs 'inactivity') does not guarantee converse self-reported attitudes. Although some of the measures we used (e.g. SRHI in pilot study 4.1, our HWK goal commitment measure in study 6.1) have been validated, these and others including our measure of reactance (study 6.1, chapter 7), measures of implicit food attitude (HTAS, study 5.1), measure of smartphone addiction (study 5.3) and use of semantic differentials (studies 5.1, 6.1 and 7.1) are still areas of active research. There is also debate about the use of reaction time data to measure implicit activation [Blanton et al. 2015].

[10] Not reported elsewhere for reasons of brevity.

The short-term nature of the experiments partly reflects the practicalities of running HCI experiments in CS departments with students; and partly our approach to determine the short-term effects of NDBCIs to identify the most promising areas of future research.

The majority of our experiments used randomisation of stimuli rather than a set stimulus list. Although our statistical approach allows us to incorporate random reactions to stimuli by-participant, not all of our models converged with this added. Therefore, our analysis does not always allow us to disambiguate order effects from intervention effects. The majority of our experiments also used between-subjects experiments because we wished to avoid carry-over effects and use a control group to establish baseline responses (e.g. experiment 6.3). However, given our relatively small numbers of participants, this has limited the explanatory power of our experiments. Lastly, not all of our experiments included a control group (e.g. pilot study 4.1, study 6.4).

In terms of statistical approach to demonstrate subliminal effects, we note ongoing debate about the most appropriate method of statistical analysis of such experiment data [Sand and Nilsson 2016].

Much of our data was noisy (e.g. reaction times in the semi-controlled study 5.3 and in the Stroop in-the-wild results); reaction time data is inherently noisy, and we had the additional distraction of the more life-life environments acting on our participants.

Future research

Table 8:1 summarises our suggested future work arising from open research questions remaining in each application area from our experiment chapters and across the broader areas of reactance, context-aware technology and ethics.

Area	*Future Research*
Implementation Intentions (Chapter 4)	**Expand context-awareness**: test Implementation Intentions triggered by motion-aware Bluetooth Low-Energy beacons to test whether qualitative interest in their use from elicitation survey 4.2 is supported in-the-wild without issues of intelligibility and reactance.

Area	*Future Research*
Cognitive Bias Modification (Chapter 5)	**Tailoring** (healthy eating domain): user-chosen image targets would reflect individual user preferences. Using photos of foods in naturalistic contexts may result in a stronger effect since context forms part of the food-cueing process [Adams et al. 2015; Hanks et al. 2012; Wansink 2010]. **Tailoring** (smartphone problematic use domain): enabling users to replicate their bedside tables, with images of their own phone and books.
Subliminal priming on smartphones (Chapter 6)	**Generalisability:** repeat feasibility study in-the-wild on participant devices to gauge the impact of in-use devices on the results.
Strategic, collaboratively-set autonomous goals (Chapter 7)	**Validation:** determine the behavioural impact high-cognitive-resource setting at the outset coupled with medium-cognitive-load rehearsal approaches in long-term user study. **Identifying cues:** how can interventions best identify 'good' Implementation Intention candidate cues? **Intelligibility:** how can interventions support users to create effective Implementation Intentions of appropriate specificity from multiple candidate cues, employing chaining and clash-detection strategies?
Reactance	Explore the boundaries of reactance in NDBCIs, particularly with respect to behavioural commands issued by smartphones. Determine whether pick-and-mix (N)DBCIs can help to reduce reactance? Explore how DBCIs can automate goals to trigger goal activation without causing reactance, forgetting or inattention.
Context-aware technology	Trigger hunters; Self pick-and-mix (as above)
Ethics	Research how to counter the use of NDBCI techniques by advertisers.

Table 8:1 Future work themes

We have also derived a series of interaction design considerations s from lessons learned from our explorations of NDBCIs to help guide this future research plan.

DESIGN GUIDELINES FOR NDBCI

SIMPLIFY BEHAVIOUR AND CONTEXT

NDBCI should start by supporting users to clearly identify their target response [Michie et al. 2014a]. To promote faster automaticity, the target response should be as simple as possible [Lally and Gardner 2013; Wood and Neal 2007]. Likewise, NDBCIs should select the smallest possible set of salient cues to form a 'stable context' as a habit trigger, since simpler context causation models support faster automaticity than complex ones [FitzGerald et al. 2014].

NCDBIs can play an important role in identifying and avoiding cue clashes. Cues associated with multiple responses are likely to cause response conflict, triggering arbitration and conscious Type 2 resources, and thus hinder automaticity [Wood and Neal 2007]. For unwanted automatic behaviours, NDBCIs need to isolate the particular context cue(s) that trigger an unwanted response. We have shown that this level of rich context-detection is not trivial, and getting it wrong risks user reactance. Yet as context-detection technology and algorithms improves NDBCIs could play a key role in identifying introspectable trigger cues for their users.

TYPE 1 / TYPE 2 TAILORING

It is a general DBCI principle that interventions should adapt to individual users [Ijsselsteijn et al. 2006; Ranfelt et al. 2009; Orji et al. 2017]. The BAF requires a specific form of tailoring because individuals vary in relative influence of Type 1 and Type 2 behaviours [Sladek et al. 2006]. For example, one individual may be more "impulsive" or susceptible to temptations than others. In these circumstances, a DBCI may need to intervene earlier in the unwanted behaviour process, e.g. by altering the context to try to prevent a user from buying tempting snacks in the first place. Individual users at different points in the behaviour change process may also require different sorts of intervention. For example, as we argued in Chapter 7, in the early stages of habit formation via Implementation Intentions, a user may need a higher level of support via intention rehearsal and reminders than when automaticity emerges.

Design for Type 1 and Type 2 congruence

Recent research suggests that the most effective DBCIs may be those that influence Type 1 and Type 2 processes in congruence [St Quinton and Brunton 2017]. We have argued that a likely failure of many interventions is the focus on Type 2 processes, undermined by incongruent Type 1 default processes. We caution against a similarly myopic focus on Type 1 processes *only*. For example, priming can only be successful where a person already has relevant cognitive constructs motivated towards the given behaviour [Strahan et al. 2002]. This may explain our lack of results from study 6.1: although we recruited participants that were motivated towards being more physically active, there was the additional motivation of a small honorarium which may have skewed recruitment. Congruence-focused DBCIs should support user behaviour change regardless of levels of user attention, deliberative resources and individual differences in Type 1 / Type 2 dominance.

Design for persistence

Behaviour change is a long-term process. Automatic behaviour only emerges over time, so interventions need to be viable over the longer term. NDBCIs should also aim to complement and augment how our brains work [Rogers 2006] to leverage Type 1 processes, rather than leaving users dependent on their machines [Renfree et al. 2016]. Just-in-time interruption strategies risk dependency and reactance. DBCIs should anticipate technology and user failures, including failures in a user's Type 2 processes due to limited conscious cognitive resources. As we argued in Chapter 7, a good alternative to just-in-time strategies is to shift cognitive load to pre-training and rehearsal.

Design ethically

Ethics requirements are not new, but we have outlined how NDBCIs raise additional concerns. They aim to create automatic behaviour resistant to change, so it is critical people can give informed consent. Users should in principle control their DBCIs, rather than the other way round [Rogers 2006]. However, this principle is often violated with non-digital BCIs e.g. tobacco packaging warning messages [Peters et al. 2013].

Safety is an ethical issue when delivering disruptive interventions to activate Type 2 processes. Disrupting users under cognitive load in potentially dangerous tasks (e.g. driving) is problematic. Using existing Type 1 triggers can also be dangerous, for example, triggering fear-based 'flight' responses as used in Zombies, Run! [zombiesrungame 2015] in inappropriate contexts (e.g. crossing the road). Most of our experiments were designed to avoid cognitive load at goal activation time.

Privacy is a particular issue where systems disclose automatically-sensed information to others, e.g. for off-device computation. The fusion of real-world sensing with social networks means users have limited control over how they are represented to their social network contacts [Efstratiou et al. 2012].

Finally, it remains unclear who bears responsibility for the effects of DBCIs: the end-user or the system designer [Verbeek 2009]? The question is pertinent for configurable systems due to *unintended* consequences: for example, what if a user with an eating disorder alters a cue-valence-altering system to devalue all foods instead of just unhealthy foods? Starting with asking "*What's the worst that could happen with this intervention?*" is a good strategy.

Design for reactance

DBCIs should only deliver just-in-time behavioural directions (i.e. those that directly threaten users' behavioural autonomy) when the system is confident that the timing is appropriate. Where this is not possible, interventions should consider alternatives such as rehearsal, which can be delivered at a time of the user's choosing.

Contributions summary

Novelty

To our knowledge we have presented the first framework to analyse opportunities for technology to intervene to change behaviour using Dual Process Theory, modern habit theory and Goal Setting Theory. We have presented the first context-aware Implementation Intention intervention on smartphones, the first intervention to use CBM in an incidental way on smartphones, the first intervention to apply CBM for smartphone addiction, the first CBM on Tabletops, and the first intervention exploring subliminal priming in depth on smartphones both in-the-wild and in semi-controlled conditions.

Specific contributions

This thesis contributes to HCI and digital behaviour change knowledge by establishing an illustrative framework to explore behaviour change technology that targets automatic behaviours including habits. It provides a theoretical and empirical basis for interventions that consider nonconscious influences on behaviour. This consideration of nonconscious processes is crucial to designing effective DBCIs for three main reasons. Firstly, nonconscious behaviour is common in everyday life in

multiple domains. Secondly, reasoned-action theories and corresponding Type 2 techniques alone are unable to achieve lasting behaviour change in the presence of strong habits and other automatic behaviours. Thirdly, we have identified multiple opportunities for pervasive computing technology to deliver interventions that can target Type 1 processes.

We addressed two main questions: what are the nonconscious influences on our behaviour, and how can we apply nonconscious behaviour change techniques using technology? We answered Question 1 by analysing common behaviour change theories, and synthesising the illustrative Behaviour Alteration Framework from Dual Process Theory, Goal Setting Theory and modern habit theory. It shows how behaviour is strongly influenced by environmental and physiological cues, which trigger implicit memory stores to generate behavioural impulses. Where limited Type 2 resources are low, these impulses drive the default behaviour. We answered Question 2 by mapping a series of strategies to the intervention points identified in the BAF, then running a series of pilots and studies to explore a sub-set of these strategies including Implementation Intentions, CBM and subliminal techniques, on platforms including smartphones and a Tabletop. Overall, we found that despite the strong theoretical underpinnings, and empirical support for intervention strategies from psychology labs, the impact of interventions was either not evident, or small and somewhat fragile under in-the-wild and semi-controlled conditions. Therefore, we argue that the most promising strategy of future research is to focus on understanding how best to deploy multiple NDBCI strategies at different levels of cognitive load, by shifting high-cognitive-load tasks away from goal activation to focus on embedding that goal at creation time, and providing medium-cognitive-load rehearsal opportunities such that the goal becomes autonomous and can therefore be triggered unobtrusively by the user's context in the future.

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10. APPENDIX

A1 Chapter 4 Implementation Intentions

4.1 Pilot

Consent form

Developing mobile application to promote Implementation Intentions as a trigger for building a habit

Experiment Purpose & Procedure

The purpose of this experiment is to evaluate the impact of mobile application that applies the theory of Implementation Intentions for building new habit.

The experiment is divided into three different phases. In the first phase, you need to complete a pre-questionnaire. In the second phase, you will be asked to install an app in your phone. The app will let you to create a specific goal that you want to build as a habit. You have to select at least one situational cue for the goal you want to create. When a condition meets the contextual cues you have defined before, a notification will be triggered to remind you in pursuing your goal. The third phase of this research is you will be asked to complete a post-questionnaire.

Confidentiality

The following data will be recorded in a file in your device: the goal and cues you have created, sensor data from your mobile phone (including: accelerometer, location, wi-fi, phone and connection state, app log, battery, and screen on/off state).

All data will be coded so that your anonymity will be protected in any research papers and presentations that result from this work.

If you are interested to find out the result from this research, you can contact the researcher:

Record of Consent

Thank you for your interest in our research. Your signature below indicates that you have understood the information about the experiment to evaluate the impact of mobile application that applies the theory of Implementation Intentions for building new habit and consent to your participation. The participation is voluntary and you may refuse to answer certain questions on the questionnaire and withdraw from the study at any time with no penalty. If you have further questions related to this research, please contact the researcher.

Participant Date

Researcher Date

Questionnaires

PRE – SELF-REPORT HABIT INDEX SUB-SCALE

This questionnaire will ask you about a behaviour that you want to do and make it as a habit. Firstly, you need to write a specific behaviour that you want to do (for example: eating fruit when having breakfast, drinking a bottle of water when having lunch, running for 15 minutes at afternoon, etc). Secondly, you need to answer the following questions by choosing the right scale that represents your perception towards a behaviour that you are intending to do. Below is the guidance on the degree of agreement from each scale:

1 – Strongly disagree
2 – Disagree
3 – Somewhat disagree
4 – Neither agree or disagree
5 – Somewhat agree
6 – Agree
7 – Strongly agree

Name *

Email address *

What kind of behaviour do you want to make as a habit? *

1-7 Likert items:

- ^ I do that behaviour automatically *
- ^ I do that behaviour without having to consciously remember *
- That behaviour makes me feel weird if I do not do it *
- ^ I do that behaviour without thinking *
- That behaviour would require effort not to do it *
- ^ I start doing that behaviour before I realise I am doing it *
- I would find hard not to do that behaviour *
- I have no need to think about doing that behaviour *

^ are Self-Report Behavioural Automaticity Index items

POST SELF-REPORT HABIT INDEX SUB-SCALE

As you already had the intention to build a new habit, this questionnaire will ask your progress in forming the habit. These items will ask your perception towards a new behaviour that you want to make it as a new habit.

Questionnaire items as above

SYSTEM USABILITY SCALE

The following questions will ask your perception towards the Implementation Intentions app as a tool to form a new habit.

Likert items 1-5:

- I think that I would like to use this system frequently. *
- I found the system unnecessarily complex. *
- I thought the system was easy to use. *
- I think that I would need the support of a technical person to be able to use this system. *
- I found the various functions in this system were well integrated. *
- I thought there was too much inconsistency in this system. *
- I would imagine that most people would learn to use this system very quickly. *
- I found the system very cumbersome to use. *
- I felt very confident using the system. *
- I needed to learn a lot of things before I could get going with this system. *

4.2 Follow-up survey

Consent

The following questionnaire seeks to understand more about habits to try to support people to change their behaviours as part of research at the HCI Centre at the University of Birmingham, UK. Please first think about any bad habits you have formed (i.e. repetitive behaviour that you may find it difficult to control) and what new habits you would like to form. Then read each question carefully and answer it as truthfully as you can. There are no correct or incorrect responses; we are simply interested in your personal point of view. Your data will be stored confidentially and in accordance to University of Birmingham policy. If you have any questions about the survey, please contact the lead researcher [redacted] At the end of the survey, you will have an option to enter your email address for a prize draw of a £15 Marks & Spencer voucher. Your email address will be used for prize draw purposes only. Thanks again for participating.

By continuing, I confirm that I am over 18 years of age, and I understand that I can withdraw at any time.

Demographics

1. What is your age?
2. Gender
3. Approximately how many times do you unlock your smartphone each day?
4. What is your profession? If you are a student, please state level (e.g. Masters, PhD) and subject.

Environmental triggers

The following questions seek to understand which environments may trigger bad and good habits, and explores the use of technology proximity triggers placed in those environments to try to support people to change their behaviours. Please think about any bad habits you have formed (i.e. repetitive behaviour that you may find it difficult to control) and where you perform them, and any new habits you wish to form and where you want to form them.

1. Imagine that you could place proximity triggers in your workplace or the immediate surrounds, so that you could be alerted when you are near it. Where would you place them?
2. Why did you choose those places?
3. If you had an app on your phone that responded to the proximity trigger, how should it alert you?
4. What would the app say?
5. What other information might the app need (e.g. only alert you at a certain time of day)?
6. How successful do you think this might be to change your behaviour?
7. Why do you think this would be successful/not successful?
8. Where would you place similar proximity triggers at home, and why?
9. Any other comments?

A2 Chapter 5 Cognitive Bias Modification

5.1 Accept The Banana

Elicitation study instructions & Consent form

Thank you for your interest in our research: we really appreciate people helping us out with our work.

Experiment Purpose & Procedure

The purpose of this experiment is identify the gestures that people would use to reject or accept objects in mobile devices.

The experiment consist of 10 images (triangles and rectangles), during you will be asked to perform any kind of gesture in the mobile phone to accept or reject the figures.

Please note that the task is not a test of your personal intelligence or ability. The objective is to test the usability of some gestures in order to use it to develop an application to reject and accept some features.

Confidentiality

The following data will be recorded: gestures performed in the mobile device All data will be coded so that your anonymity will be protected in any research papers and presentations that result from this work.

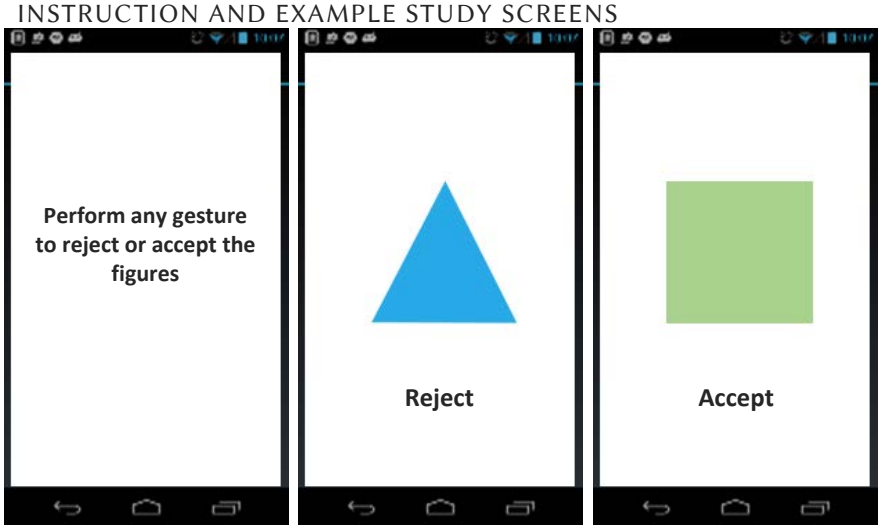
Finding out about result

If interested, you can find out the result of the study by contacting the researcher

Record of Consent

Your signature below indicates that you have understood the information about the experiment to identify common gestures for mobile devices and consent to your participation. The participation is voluntary and you may refuse to answer certain questions on the questionnaire and withdraw from the study at any time with no penalty. If you have further questions related to this research, please contact the researcher.

INSTRUCTION AND EXAMPLE STUDY SCREENS



MAIN STUDY INSTRUCTIONS & CONSENT FORM

Experiment to evaluate the effects of CBM-A modifying bias towards healthy food using mobile technology

Experiment Purpose & Procedure:

The purpose of this experiment is evaluating the extent in which attentional bias towards healthy food can be changed using mobiles phones. The experiment is divided into three phases. In the first and third part you will complete a questionnaire. In the second part you will be asked to install an app in your phone. The app will trigger a task when the screen turns on which will overlie the lock screen. You will be asked to perform a gesture to accept healthy food (check mark ✓) or a gesture to reject unhealthy food (cross mark ×). You will have three chances to perform the correct gesture. When you perform the right gesture or after the third attempt the task will be closed.

Since the task is before your lock screen you will have to perform a double-unlock. However, to avoid it you can disable your existing locking.

Confidentiality

The following data will be recorded in a file in your device: date, time, picture, gesture, and number of attempts.

All data will be coded so that your anonymity will be protected in any research papers and presentations that result from this work.

Finding out about result

If interested, you can find out the result of the study by contacting the researcher

Record of Consent

Thank you for your interest in our research: we really appreciate people helping us out with our work. Your signature below indicates that you have understood the information about the experiment to evaluate the effects of CBM-A modifying bias towards healthy food using mobile

technology and consent to your participation. The participation is voluntary and you may refuse to answer certain questions on the questionnaire and withdraw from the study at any time with no penalty. If you have further questions related to this research, please contact the researcher.

Online attitude questionnaire

DEMOGRAPHIC QUESTIONS

1. What is your age?
2. Gender
3. Approximately how many times do you unlock your smartphone each day?
4. What make and model is your phone?
5. What is your native language?
6. What is your profession? If you are a student, please state level (e.g. Masters, PhD) and subject.
7. Health declaration: I have no known health issues that mean I should not be more active
    a. I have no health issues I have no health issues
    b. I'm not sure, or I do have some health issues I'm not sure, or I do have some health issues
8. Please enter your email address. This will only be used to contact you about the experiment and for no other purposes.

THE HTAS GENERAL HEALTH INTEREST SCALE (7-POINT LIKERT SCALES)

Please choose the appropriate response for each item:

a. The healthiness of food has little impact on my food choices (R) .
b. I am very particular about the healthiness of food I eat.
c. I eat what I like and I do not worry much about the healthiness of food (R).
d. It is important for me that my diet is low in fat.
e. I always follow a healthy and balanced diet.
f. It is important for me that my daily diet contains a lot of vitamins and minerals.
g. The healthiness of snacks makes no difference to me (R).
h. I do not avoid foods, even if they may raise my cholesterol (R).

THE HTAS TASTE-RELATED FACTORS

Craving for sweet foods

Please choose the appropriate response for each item:

a. In my opinion it is strange that some people have cravings for chocolate (R)
b. In my opinion it is strange that some people have cravings for sweets (R)
c. In my opinion it is strange that some people have cravings for ice-cream (R)
d. I often have cravings for sweets
e. I often have cravings for chocolate
f. I often have cravings for ice-cream

Using food as a reward

a. I reward myself by buying something really tasty.
b. I indulge myself by buying something really delicious.
c. When I am feeling down I want to treat myself with something really delicious.
d. I avoid rewarding myself with food (R).
e. In my opinion, comforting oneself by eating is self-deception (R) .
f. I try to avoid eating delicious food when I am feeling down (R).

Pleasure

a. I do not believe that food should always be source of pleasure (R) .
b. The appearance of food makes no difference to me (R) .
c. When I eat, I concentrate on enjoying the taste of food.
d. It is important for me to eat delicious food on weekdays as well as weekends.
e. An essential part of my weekend is eating delicious food.
f. I finish my meal even when I do not like the taste of a food (R).
g. Food attitudes

HEALTHY AND UNHEALTHY FOOD PICTURE RATING

Rate the pleasantness of each food (7-point Likert scale from extremely unpleasant to extremely pleasant).

a. Apple
b. Soft drinks
c. Water
d. Burger
e. Avocado
f. Tomato
g. Banana
h. Doughnut
i. Pizza
j. Ice cream
k. Beer
l. Cake
m. Fries
n. Muffin
o. Potato crisps
p. Broccoli
q. Cabbage
r. Orange
s. Peach
t. Strawberry

Semi-structured interview questions

- How you feel using the app?
- What was annoying?
- What was helpful?
- What do you think about using these technologies to help people in their habits?
- Which other bad habits can we change using this kind of apps?
- There is anything else that you think is important to mention?

5.2 Follow-up survey

Consent

Same as 4.2 Consent

Demographics

Same as 4.2 Demographics

Selecting and deselecting items

Research has shown that repetitively selecting or deselecting items make that item more or less available in memory. This may help people to overcome a bad habit triggered by a cue item and/or help them form a good habit triggered by a cue item. For example, a smoker might be asked to swipe away images of cigarettes, and swipe towards them an image of chewing gum, or someone wishing to eat more healthily might choose images of celery and ignore images of a chocolate biscuit.

1. What pairs of select/deselect items would you choose in a similar training scenario? Please give examples of paired bad-good items e.g. cigarette-chewing gum, chocolate-apple, sofa-sneakers. Give as many examples as you think would be useful to you.
2. Why have you chosen these pairs?
3. What words would you use instead of “select” and “deselect”?
4. How successful do you think this sort of select/deselect training might be to change your behaviour?
5. Why do you think this would be successful/not successful?
6. Any other comments?

5.3 Push away the smartphone

Consent

The following questionnaire seeks to understand more about smartphone addiction and ways to counter this problem, as part of my summer project for the MSc in Human Computer Interaction at the University of Birmingham, UK.

Please first think about your daily smartphone usage and habits. Then read each question carefully and answer it as truthfully as you can. There are no correct or incorrect responses.

Your data will be stored confidentially and in accordance to the University of Birmingham policies.

If you have any questions about the survey, please contact me at
Thanks again for participating.

By continuing, I confirm that I am over 18 years of age, and I understand that I can withdraw at any time.

Demographics

1) Age
2) Gender
3) What is your profession? If you are a student, please state level (e.g. Undergraduate, Masters, PhD) and subject.
4) Approximately how many hours do you spend on your smartphone per day?
5) Approximately how many times do you check your smartphone each day?
6) Do you think you have maladaptive dependency or addiction over your Smartphone usage?
    a) Yes, I'm addicted to my Smartphone
    b) No, I'm not addicted
    c) I don't know

Smartphone Addiction Scale (SAS-SV) [Kwon et al. 2013]

For each question please rate the answer according to how true you feel it is for you (6-point Likert):

1) I miss planned work due to my Smartphone use
2) Due to my Smartphone use, I can find it hard to focus while working, doing assignments or attending classes
3) I feel pain in the wrists or at the back of the neck while using a Smartphone
4) I would not bear not having a Smartphone
5) I feel impatient and worried when I am not carrying my Smartphone
6) I have my Smartphone in my mind even when I am not using it
7) I will never give up using my smartphone even when my daily life is already greatly affected by it
8) I constantly check my Smartphone so as not to miss conversations between other people on Twitter, Facebook or other Social Networks
9) I find myself using my Smartphone longer than I originally intended
10) The people around me tell me that I use my smartphone too much.

A3 Chapter 6 Subliminal priming

Experiment 6.1 Instructions & Consent form

PARTICIPANT INFORMATION SHEET –active :) experiment

Thank you for your interest in participating in our research. Please read this form carefully.

Research study title: Pervasive persuasive: interventions to change habitual behaviour

Description: A study to investigate active behaviour goals supported by mobile devices.

What participation entails:

Thank you for your interest in participating in the study. The participation in this research is entirely voluntary and you are free to withdraw at any time. This research will be conducted via your browser and your own Android mobile phone. You will need a phone with Android version 4.1 (JellyBean) or greater without a custom lock screen. Please ensure you have enabled the phone's default lock screen (PIN or pattern) for the duration of the experiment. This research will run over 1 week, although your total participation time should be around 1 hour.

You will be asked to do the following:

- Follow an online procedure to form an activity goal –you will be guided through the steps to form a simple, specific goal to increase your activity (e.g. walk for at least 1 hour a day) for the duration of the experiment.
- Complete a brief survey online (approx. 10 mins).
- Install an app onto your phone which tracks your lock/unlock usage (no other personal information such as location or call or messaging activity is tracked) and which may give you goal prompts when you unlock your phone.
- Complete a brief colour-naming task on your phone (approx. 5 mins)
- 1 week later, repeat the colour naming task and a final survey online (approx. 15 mins max).

Data recording your interactions with the app and your phone (including no location data, and no personal data other than an assigned ID) will be sent via Wi-Fi to be stored in a secured database in Computer Science.

Please be aware that this monitoring and data transfer uses battery: you may need to charge your mobile every day.

You will receive an Amazon voucher of £5 for completing the research, including running the app on your phone for 1 week, and completing the task and surveys.

Mobile Application

The research team has made every effort to test the application before the experiment. However, problems and software bugs do occur. If you have difficulties then you should contact the research team for assistance via [redacted] describing the problem as clearly as you can.

The mobile application needs to exchange a small amount of data with our servers from time to time. To do this it needs a data connection. This can be either be via WiFi or your mobile data network. Be aware that, just like any other mobile application, this will be included in whatever data allowance you have and thus may incur charges depending upon your mobile tariff.

If for any reason you feel the application is causing immediate problems then please uninstall the application and contact the research team at

Again please be aware that you are free to withdraw from the experiment and uninstall the application at any point. If you withdraw unfortunately we will not be able to provide you with the £5Amazon voucher.

In addition to withdrawing from the experiment, you can also request that your data is removed from the experiment: if you request this, any data gathered up until that point will be destroyed.

Confidentiality/anonymity and data security

All of your data will be stored confidentially and given a unique identification code.

The data we collect will be stored securely. Only members of the project team will have access to this data. Data will be stored as per University policy and any personal data gathered for recruitment will be destroyed upon completion of the experiment.

Results of the study

The results of the study will be written up for academic publication. This research may also be presented at national and international conferences and events. If you would like feedback from the study feel free to email the lead researchers below who will be able to help with your request.

For further information: If you would like any further information about the study please email

Experiment 6.1 Goal setting instructions

Now it's time for you to set an active :) goal that you will try to stick to during the experiment.

Goal setting theory suggests that the best sort of goals are clear and specific (i.e. "I will walk for 30 minutes total a day" rather than "I will try and walk more each day") and somewhat hard to achieve - so please choose an active :) goal that will stretch you, rather than one you are sure that you can easily achieve. You should also be committed to achieving your active :) goal.

Please take a few minutes to think about a suitable active :) goal.

Once you have chosen your active :) goal, please write it in the box below.

Experiment 6.3/6.3B Instructions & Consent Form

Thank you for supporting our research :). Please read this page carefully before you start - it sets out what the task is, what data we gather and how we use the data.

Research study title: Visual discrimination tasks on smartphones

Research description: A study to investigate visual discrimination tasks on mobile devices

Task details

1. We'll first ask some brief demographics details.
2. The main task is a brief (~5 mins) set of simple image choices. You'll be shown images one by one for a very short space of time, then asked to choose between two images, one of which you may have been shown before. Do not worry if you can't see the image. You will also get a chance to have a practice first.
3. Your participation is entirely voluntary and you are free to withdraw at any time.

Confidentiality/anonymity and data security

All of your data will be stored confidentially and given a unique identification code. The data we collect will be stored securely. Only members of the project team will have access to this data. Data will be stored as per University policy.

Results of the study

The anonymised results of the study will be written up for academic publication and may be presented at conferences and events. For further information: please email

If you're happy with the above, and you are 18 years or over, please tap the button below to proceed. Thanks again for your help :).

Experiment 6.4 Consent form

Thank you for supporting our research :). Please read this page carefully before you start - it sets out what the task is, what data we gather and how we use the data.

Research study title: Number sorting tasks on smartphones

Research description: A study to investigate number sorting tasks on mobile devices

Task details

1. We'll first ask some demographics details.

2. The main task is a brief (~10 mins) number sorting task. You'll be shown a number between 1 and 9 and asked to categorise it as less than or more than 5.
Full instructions will be given and you will get a chance to have a practice first.

3. Your participation is entirely voluntary and you are free to withdraw at any time

Confidentiality/anonymity and data security: All of your data will be stored confidentially and given a unique identification code. The data we collect will be stored securely. Only members of the project team will have access to this data. Data will be stored as per University policy.

Results of the study: The anonymised results of the study will be written up for academic publication and may be presented at conferences and events. For further information: please email

If you're happy with the above, and you are 18 years or over, please tap the button below to proceed. Thanks again for your help :).

Experiment 6.4 Instructions

Number sorting task

A number between 1 and 9 will appear in the centre of the screen. Your task is to classify the number as less than or greater than 5.

If the number is less than 5, press the left hand less than “<” button

If the number is more than 5, press the right hand more than “>” button

If a '#' symbol appears, freely and randomly choose a button to press. Please try to avoid a fixed pattern in your free choice responses (e.g. don't do left, then right, then left) and only decide which button to press when the '#' appears rather than pre-planning.

Each trial begins with a neutral visual symbol to warn you that the number is about to appear.

You'll have 1.5 seconds to respond, and the app will tell you if you get the answer wrong or you time out.

When you are ready for a practice run, tap "START".

EXPERIMENT 6.4 VISIBILITY TASK INSTRUCTIONS

Well done, that's the end of the first part of the experiment!

A little more about the task you've just completed: the images you were shown just before the target number actually contained a 'prime' - another number (1,2,3,4,6,7,8 or 9), presented for a very short space of time (~35ms) in between 2 letter masks.

You were shown a letter mask, then a prime, then another letter mask and then the target number as shown below:

For the final task, we will re-run a small part of the experiment but this time try to see ONLY the prime, and answer whether it was less than or greater than 5.

Ignore the final target number that you were concentrating on in the first task.

If you can't see the prime, which only appears for a very short space of time, please just guess.

There are only 3 blocks in this test.

Tap RESUME to start.

A4 Chapter 7 Qualitative analysis of goals

Raw goals data

id	*goal*
1	I will walk for 60 minutes a day and swim for 45 minutes twice a week
2	I shall walk a minimum of 5 minutes a day, every day of the week.
3	I will do 30 press ups a day. 15 morning and evening
4	i will walk for 90 minutes each day
5	I will either walk for an hour each day, OR do more vigorous exercise for 20 minutes (jog/cycle etc) - depending upon my time commitments that day
6	I will walk 1 hour per dag
7	I will leave home at 7.20am Monday- Friday to get to university
8	I will run 3 times in the next week and have totalled more than 25km by Sunday.
9	I will do sit ups every day for 30 minutes.
10	I will be active (walking or gym) for 1 hour total a day
11	I will walk for 60 minutes a day
12	I will do 5 sets of 10 push ups each day
13	I will run 3 times a week for 30 minutes each
14	I will walk for 30 mins total per day
15	Walking or running at least 20 minutes a day.
16	I will complete my push up routine every day
17	To walk for 90 minutes total each day
18	Walk everyday for 45 minutes or more
19	I will walk 1 mile a day
20	I will do 100 push ups a day, 5 times a week.
21	Walk for 20 minutes for 3 days in the week.
22	Walk for 20 minutes a day
23	I will walk for 30 minutes each day.
24	I will do two 15 mins walks a day.
25	I will perform vigorous exercise 5 days a week
26	At work, I will not take the lift but instead, take the stairs.
27	Have at least 4 Parkour session per week (each should last around 1 hour)
28	I will go for a run every other day
29	I will walk for 1 hour total a day
30	I will walk for a total of 45 minutes each day
31	Instead of walking, I will go and come back from the gym running. About 15 minutes running.
32	I will drink 8 glasses (or equivalent) of water a day
33	I will do 30 minutes fitness exercises each day i.e pilates
34	I will complete physio exercises daily for 30 mins
35	I will walk or run 20000 steps a day
36	I will try and walk 10000 steps each day
37	To walk or run for 30 minutes each day
38	I will walk for over an hour every day this week
39	Walk for 30 minutes a day (outside of commuting to lectures)
40	i will walk 30 mins a day
41	i will walk no less then 30 min a day

id	*goal*
42	I will power walk for 20 minutes a day on top of my normal walking daily
43	Go to two spinning classes (>45 min each) per week.
44	I will walk over 10,000 steps every day
45	Complete 10000 steps a day
46	I will reach 8000steps every day
47	I will walk for 60 minutes total a day
48	I will do a 10 minute high intensity workout each day.
49	I will go swimming before work three times this week.
50	High intensity exercise 30 minutes at least a day
51	I will do yoga on 4 days
52	I will cardio train (run skip and cycle) for 30 minutes total a day.