A Cognitive Design Space for Supporting Self-Regulation of ICT Use

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Abstract

A majority of users of smartphones and laptops report that they struggle with effective self-control over their device use. In response, HCI research - as well as a rapidly growing commercial market for 'anti-distraction tools' - has begun to develop apps, browser plugins, and other tools that help users understand and regulate their use. The extensive literature on the mechanics of self-regulation from cognitive neuroscience and behavioural economics might help guide this work. However, so far the emerging HCI work has drawn on a very limited subset of self-regulatory models, in particular Social-Cognitive Theory. Here, we draw together main insights from a broader spectrum of basic research on the mechanics of self-regulation in a simple framework. We use the generated model to analyse interventions in a sample of 112 existing anti-distraction tools, and hope it may contribute a useful alternative view of the design space for UI features that support self-regulation.

Author Keywords

Self-regulation; self-control; non-use; distraction; attention; cognitive models

ACM Classification Keywords

H.5.m. [Information Interfaces and Presentation (e.g. HCI)]: Miscellaneous

Introduction

Smartphones and laptops give users access to an astonishing range of tasks anywhere, anytime. Whereas this has many benefits, such as increased opportunities for social support, self-disclosure and intimacy [22], a growing amount of public discussion and research attention has begun to focus on downsides [1,4]: Having immense amounts of functionality instantly and constantly available makes it difficult for users to focus on their current task and avoid being overly distracted by notifications or habitual check-ins [16].

In response, HCI researchers have called for more research into intentional 'non-use' of information and communication technologies (ICTs) [4], and a substantial body of such work has now established that a majority of users feel conflicted about the time they spend with networked digital technologies [12]. Moreover, an entire commercial market niche has appeared for 'anti-distraction tools': smartphone apps, desktop applications, browser plugins and other tools that claim to help users self-regulate. For example, these operate by removing distractions from user interfaces or blocking access to them (e.g. Freedom, Newsfeed Eradicator), tracking and visualising device use (e.g. RescueTime, Moment), or rewarding intended - or punishing unintended - device use (e.g. Forest, Obtract). Some of these have become widely disseminated, with installations of e.g. the mobile app Forest numbering in the millions [10].

Our understanding of how to design for improved self-regulation of ICT use is, however, in its early days [23].

A few papers has studied select examples of commercially available tools [6,15,16] and, in a handful of others, HCI researchers have begun to design, implement and test novel ones [11,12,14,23].

This emerging work has contributed important results towards principles and guidelines for design that support self-regulation of ICT use. However, these first forays have made limited use of basic work from the behavioural neurosciences on the mechanics of self-regulation to classify, understand, and predict relevant design features. For example, Whittaker et al. [23] developed their prototype 'MeTime' based on a review of correlational research on work fragmentation paired with semi-structured user interviews; Hiniker et al. [11] based their app 'MyTime' on informal brainstorming to construct an initial design space, followed by user surveys to select the most popular ideas; and whereas Ko et al. [12] drew on a psychological model of self-regulation for their app 'NUGU', they exclusively used Social Cognitive Theory with no reference to the broader literature on the mechanics of self-regulation.

In the ongoing work presented here, we draw together main insights from the behavioural neuroscience of self-regulation, and use the resulting model to frame self-regulation struggles related to ICT use and analyse a sample of existing anti-distraction tools. The goal is to provide a cognitive description of the design space of anti-distraction tools that may bridge basic research on the mechanics of self-regulation and practical design efforts.

The behavioural neuroscience of self-regulation: A very brief summary

Self-regulation research investigates the practical attempts as well as the underlying mechanisms with which people exert control over their inner processes and external behaviour, such as suppressing undesirable impulses or sustaining concentration [5].

From a cognitive perspective, behaviour control can be divided into System 1 processes which occur rapidly, unconsciously, and in parallel, and System 2 processes which are slower, conscious, and limited by capacity, switch costs and fluctuations over time [5,20]. System 1 control is driven primarily by environmental stimuli, which gets connected to instinctive or well-rehearsed responses. System 2 control is driven by goals and rules held in conscious working memory [17].

A common view is that patterns of behaviour are represented in the brain as hierarchical action schemas that can be thought of as nodes in a network where each node has a continuous activation value [18]. Schema nodes receive input from a number of sources including top-down biases from System 2 control and bottom-up environmental triggering, and the nodes with the strongest activation value get expressed in behavior [7].

From this perspective, self-regulation is exertion of control that biases the competition between action schemas in a way that aligns inner processes and external behaviour with one's goals [7]. It is mediated by metacognitive processes that monitor other processes in the mind and exercise control when a mismatch is perceived between the desired and actual state of the world [20]. Self-regulation through System
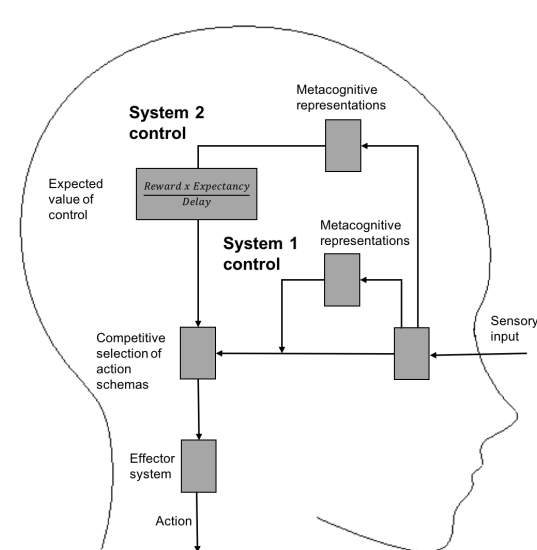

Figure 1. Main components of self-regulation. Based on [20]

2-level processes is often referred to as 'self-control' and reflects conscious efforts to align behaviour with our goals [3].

Conscious self-control efforts are not always successful. The strength of top-down biases depends on the expected value of control, which is based on the rewards, likelihood, and timing of the outcomes that might be achieved through conscious control: A wide range of studies have found that people's performance in tasks requiring top-down control is improved if they are given greater *rewards* for successful performance [5]. Performance is also greater the more *confidence* one has that attempts at control will be successful [21]. Finally, the less *delayed* the potential rewards of self-control are, the more likely is successful self-control [2].

Most of the variation in people's success at self-regulation come down to differences in their self-

Inclusion	Exclusion
Mobile app, desktop application, browser plugin, or physical accessory	Duplication of tool already located
Intended by designer to aid self-regulation of personal use of smartphone or laptop	Intended to aid self-regulation of one specific functionality only (e.g. minimalistic writing app)
Accessible in Google Play Store, Apple App store, or detailed in research paper or media	No English description of app functionality available
	Reviews suggest app is a scam

Table 1: inclusion and exclusion criteria for tool review

regulatory strategies rather than differences in their executive functioning per se: People rated highly on self-control are more likely to set up environments in which they are less exposed to temptations, and to adopt habits that align automatic System 1 behaviour control with their long-term goals, so that behaviour aligned with their long-term goals is less dependent on moment-to-moment conscious control [8].

Finally, self-regulation is an area of human behaviour where people tend to have poor self-insight. People tend to underestimate the influence of their environment on behaviour as well as overestimate the continuity between the goals of their current and future selves [19].

Applying the Model
General Insights
Viewing struggles with self-regulation of ICT use through this lens yields the following perspective on its meaning, causes, and related design features:

First, the meaning of self-regulatory difficulties is that conscious, System 2-level processing perceive a mismatch between one's past or current ICT use and one's reflective usage goals.

Second, the general cause of such mismatch is that System 1-level behaviour control is not aligned with one's reflective usage goals, and that those usage goals are either not represented in working memory at the time of action (in which case no top-down biases were applied to steer behaviour accordingly), or the expected value of control is too low to generate top-down biases strong enough to cause the desired action schemas to control behaviour.

If one's reflective usage goals are not represented at the time of use, they may have been crowded out due to limitations on working memory capacity (e.g. logging in to Facebook to send a message but have attention-grabbing content from the newsfeed replace the original goal). If the expected value of control is too low, the perceived reward associated with conscious self-control may be low (e.g. not receiving any obvious reward from inhibiting an impulse to check Facebook), confidence in one's ability to self-regulate may be low (e.g. not believing that one will be able to suppress the urge to check the site anyway), or the reward from self-control may be delayed (e.g. "checking Facebook might slow down finishing my work report, but it's a month before it's due anyway").

Third, default design of smartphones and laptops tends to give users instant and permanent access to most functionality. This should be expected to be a major reason for self-regulatory struggles, as the evidence on individual differences in ability to self-regulate suggests that relying on continuous top-down control is a poor strategy compared to restricting exposure to temptations and developing beneficial habits [8].

Classifying current anti-distraction tools
We collected a sample of current anti-distraction tools by reviewing relevant literature [11,12,13,14,23], and by searching the Google Play and Apple app stores (search terms 'smartphone addiction', 'smartphone distraction', 'addiction', 'distraction', 'motivation').

INCLUSION AND EXCLUSION CRITERIA
Our inclusion criteria aimed at identifying a sample of apps and browser plugins intended to help users self-regulate use of ICT devices (see table 1).

CODING SELF-REGULATORY MECHANISMS TARGETED

For each cognitive factor, presence of interventions targeting it in an anti-distraction tool was coded as present (1) or absent (0) based on the description, screenshots, and videos available on the app stores or papers in which the tool was described.

Interventions were coded by the author according to the following guidelines: *Perceptual input* subsumes interventions that remove or change the appearance of user interface elements (e.g. removing Facebook's news feed); *schema competition* interventions that make actions unavailable (e.g. blocking access to Facebook); *System 1 control* interventions that target habit formation or disruption (e.g. shuffling the location of an app); *System 2 monitoring* interventions that encourage setting and remembering goals, or inform the user of their behaviour; *expected value of control (EVC): reward* interventions that reward or punish behaviour (e.g. providing badges for not engaging with distracting functionality); *EVC: expectancy* interventions that target confidence in ability to self-regulate (e.g. providing encouragement), and *EVC: delay* interventions that make the utility of distractions or benefits of self-control less or more immediate (e.g. adding latency to loading of distracting websites).

RESULTS

We identified 149 candidate tools in the initial search, of which 37 were excluded after screening, leaving 112 apps in the review[1]. The proportion of apps targeting each factor is shown in Fig. 3. The interventions most commonly included in our sample of relate to System 2

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[1] Details are available via the Open Science Framework at osf.io/wuyz3

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monitoring (present in 48% of apps), perceptual input (41%), and schema competition (33%).

Conclusion

This line of work is in an early stage with many questions outstanding. In terms of the model itself, future empirical work with designers is necessary to test whether the level of abstraction at which we have described the cognitive mechanisms involved is practically useful. In terms of applying the model to analyse existing tools, the criteria for classifying which cognitive mechanisms are targeted by specific design features needs refinement. Moreover, the advantages of applying our model rather than existing taxonomies of behaviour change techniques (e.g. [9]) needs to be discussed in future work.

We hope our work may be a useful contribution which brings a novel perspective on the cognitive mechanisms underpinning cognitive control to the table.

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Figure 2 Proportions of anti-distraction tools including elements aimed at each self-regulatory factor

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