Future incentives to reduce mobile phone usage

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Abstract:

Most people would like to reduce their smartphone usage but fail to do so due to addictive nature of many smartphone applications. Building on the theory of rational addiction, we conducted two pre-registered randomized control trials that aim to reduce subject's smartphone usage by providing temporary monetary incentives and targets over a period of time. When future targets and incentives to reduce mobile usage are pre-announced, subjects conduct themselves in a forward-looking manner and reduce their mobile usage even before they are actually incentivized to do so. Subjects continue to maintain a lower usage during the incentive period and sustain that lower usage even after the incentives are removed. Using the theoretical framework of rational addiction, we show that pre-announcing future targets and incentives could be a cost-effective intervention to kick start behavioral change.

Keywords: screen time, anticipation, habit formation

Track: Consumer Behavior

1. Motivation and research objectives

Excessive smartphone usage has now become a growing concern for many individuals across the world. The average person now spends around four hours every day looking at their smartphone screen. Cross-sectional and longitudinal studies have shown negative associations between screen time and academic performance (Giunchiglia, Zeni, Gobbi, & Bignotti, 2018), performance at work (Liu, Ji, & Dust, 2020) as well as wellbeing (Twenge & Campbell, 2019) and sleep (Hisler, Twenge, & Krizan, 2020). Thus, reducing mobile screen time might be beneficial for many people. However, excessive smartphone usage is a habitual (Anderson & Wood, 2021) and addictive behavior (Alter, 2017) that is difficult to manage. Hence, cost-effective solutions to help consumers reduce screen time are needed.

In the current research, we empirically test if pre-announcing incentives for future screen time reduction can reduce screen time at the present when subjects are not yet incentivized. Our approach is based on the model of rational addiction (Becker & Murphy, 1988) which argues that people can be forward-looking and rational when forming a habit (i.e., maximizing lifetime utility by taking into consideration future consumption). According to the theory, a person is more likely to engage in a (harmful or beneficial) behavior not only if they have engaged in the very same behavior in the past (i.e., "adjacent complementarity"), but also if the person realizes the habit-forming nature of this behavior and wishes to engage in it in the future (Gruber & Köszegi, 2001). This means that people may consider the consequences of their current consumption on their future consumption. From a policy perspective, this implies that incentives paid in the future to encourage behavior change can lead people to anticipate and adapt their behavior even prior to receiving actual incentives. Thus, policy makers could cost-effectively instigate behavioral change in the present by incentivizing behavior in the future.

While empirical evidence of rational addiction has been demonstrated in the context of taxation, smoking and alcohol (Becker, Grossman, & Murphy, 1994; Gruber & Köszegi, 2001; Baltagi & Griffin, 2002) as well as social media consumption (Kwon, So, Han, & Oh, 2016), previous studies that tested the key predictions of rational addiction have typically used non-experimental time series data and relied on self-reported consumption data (Kaye, Orben, Ellis, Hunter, & Houghton, 2020). Hence, thus far, clear causal evidence of rational addiction is scarce. To address these empirical issues, we design a randomized controlled trial (RCT) to properly test whether anticipated incentives can lead to pre-emptive behavioral change (i.e., mobile phone usage reduction) based on the prediction of rational addiction. We collected individual-level panel data on daily mobile screen time over six weeks including a baseline and a post-treatment period without incentives. Rather than relying on imprecise self-reports (Kaye et al. 2020), we measured mobile usage objectively using screen time applications tailored for different mobile operating systems. As our subjects were university students, we also tracked the effect of reduced mobile usage on academic performance and other secondary well-being measures.

2. Research method

2.1 Study design

From February to April 2020, we conducted a pre-registered RCT (N = 110; 74 females; M_{age} = 21.1, SD = 2.25) at a large international university with the aim to reduce the mobile screen time of our subjects by 25% from their baseline usage, by providing monetary incentives and targets. After a baseline period of seven days, we randomized subjects into three conditions: 1) Control (C) condition, 2) Full Incentives (FI) treatment, 3) Anticipated Incentives (AI) treatment. Subjects in the C condition (N = 33) had no targets or monetary incentives for reducing their screen time throughout the study. Subjects in the FI treatment (N = 39) were paid 2€, for each day during period 1 and 2 (nineteen days in total) whenever their screen time was at least 25% lower than their baseline usage. Conversely, subjects in the AI condition (N = 38) were paid 2€ for each day only during period 2 (ten days) whenever their screen time was at least 25% lower than their baseline usage. Importantly, subjects in the AI condition were informed about their period 2 incentives and targets at the beginning of period 1 itself, nine days prior to period 2. In the post-treatment period, we removed the targets and incentives in the two treatment conditions (FI and AI) but asked subjects to continue reporting their screen time for the next seven days. Three weeks later, we asked subjects for one additional screen time report. All subjects were paid 15€ for their participation.

We collected individual-level panel data on daily mobile screen time over the entire course of the study by asking subjects to fill out an online weekly screen time report. We measured mobile usage objectively using screen time applications tailored for different mobile operating systems. As our subjects were university students, we also tracked the effect of reduced mobile usage on academic performance by obtaining GPA data from the university at the end of the academic term.

Subjects may find it hard to reduce their smartphone usage initially. However, habit formation theories (Becker & Murphy, 1988; Pollak, 1970) predict that if subjects reduce their mobile usage over a period of time, they will accumulate 'habit stock' and the new behavior pattern becomes habitual. By incentivizing subjects to reduce their mobile usage over time, our FI treatment aims to inculcate a lasting habit of using the smartphone less even after incentives are removed.

Our key intervention is the AI treatment where subjects were already informed about their period 2 target at the beginning of period 1. According to the theory of rational addiction (Becker & Murphy, 1988), subjects in the AI treatment will start reducing their usage in period 1 so they can benefit from the positive effect of habit stock, and therefore will find it easier to achieve the target in period 2 and sustain their lower usage in the post-treatment.

2.2 COVID-19 complication and follow-up RCT

Even though subjects in the AI condition anticipated and pre-emptively reduced their smartphone usage (compared to the control condition) in period 1, and showed similar reduction to those in the FI condition during the incentivized period, they did not sustain this reduction during the post-treatment period. Because the post-treatment period of our first RCT coincided with the start of the COVID-19 pandemic when the university was closed, and all classes were shifted online, the study experienced high attrition rate which might have biased our post-treatment results.

This motivated us to conduct a follow-up RCT focusing on the AI and C condition to understand if subjects in the AI condition could sustain their lower usage in the post-treatment period if certain conditions were tweaked. The follow-up RCT was conducted eight months after the first RCT when the COVID-19 situation has stabilized. To foster stronger anticipation and post-treatment effects in this second RCT, we (1) increased the duration of the incentive period to 14 days and (2) increased the target to a 30% reduction.

3. Results

3.1 First RCT

Using difference-in-difference OLS regressions, we find that subjects in the FI condition not only reduced their screen time during the incentive periods but also sustained a lower usage than the control condition during the post-treatment period (Figure 1).

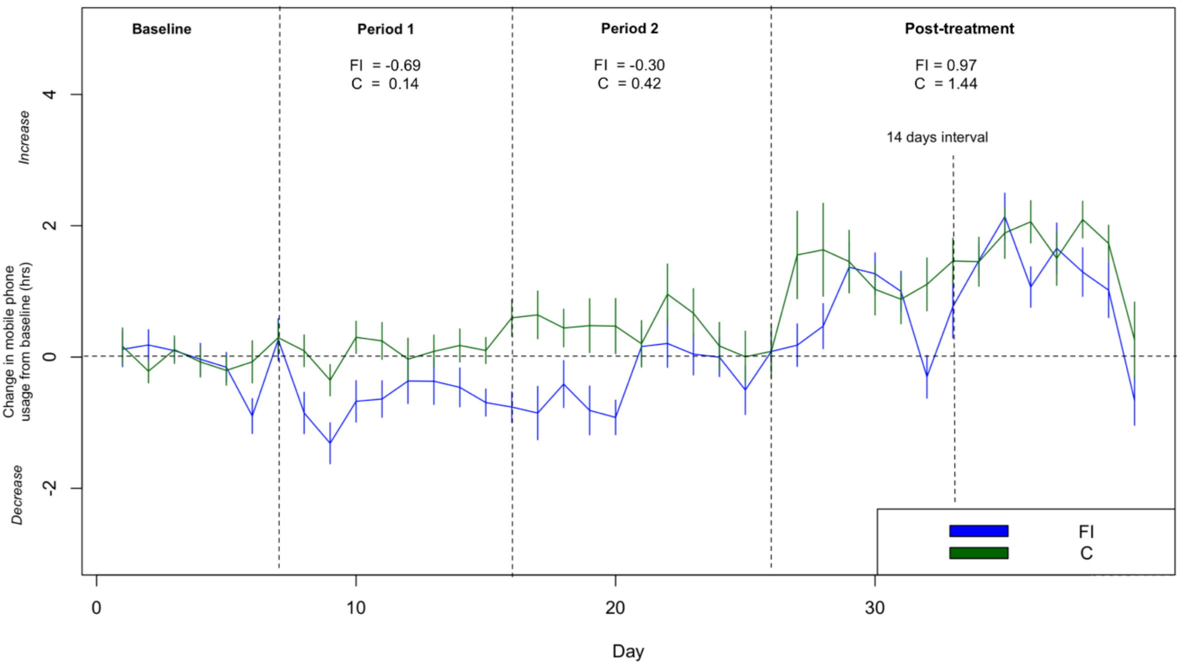

Figure 1. First RCT: Average daily change in mobile usage from baseline across conditions. Full Incentives (FI) vs. Control (C). Standard error bars are shown.

Importantly, subjects in the AI condition anticipated and pre-emptively reduced their smartphone usage (compared to the control condition) in period 1, even prior to the incentivized period 2 (Figure 2). This anticipatory reduction was primarily driven by heavy users of smartphones, i.e. those with higher baseline usage. However, subjects in the AI condition were unable to sustain their lower usage in the post-treatment period in the first RCT.

While there was no significant difference in grade point average (GPA) between conditions, we do find that subjects who reduced their mobile usage and achieved targets for more days, had higher GPA. Each additional day of target achievement (i.e., reduced usage by at least 25%) in both periods was associated with an increase in GPA by 0.035 (p = 0.03). While this evidence is correlational, it may suggest that students who reduced their usage obtained a higher GPA.

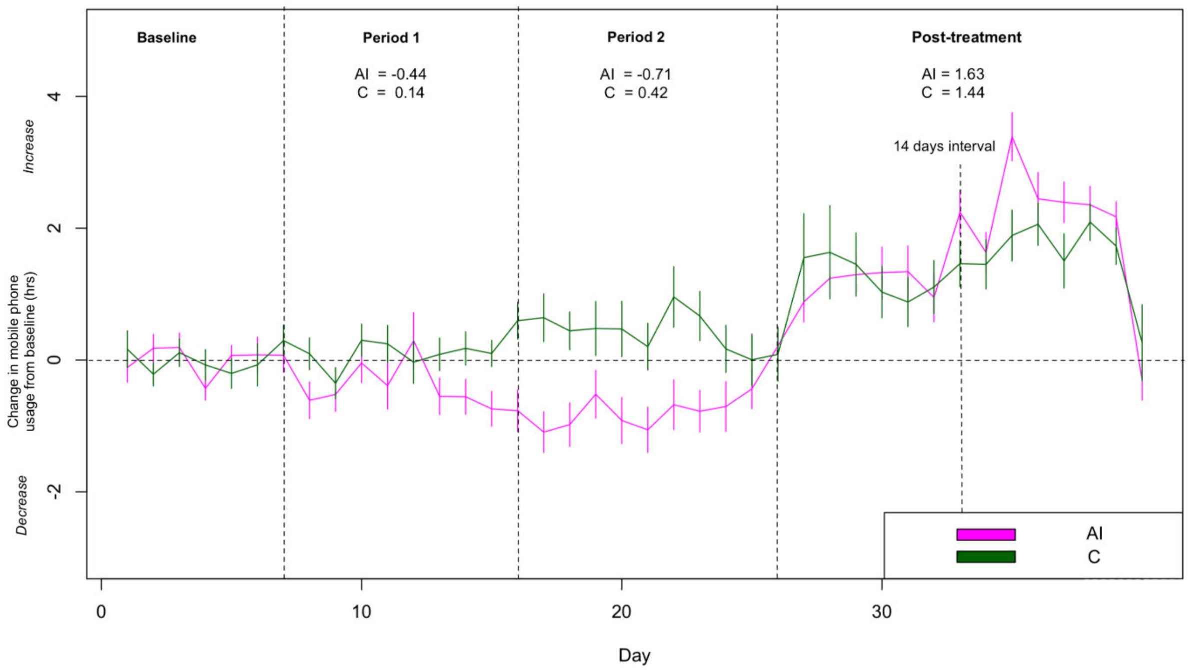

Figure 2. First RCT: Average daily change in mobile usage from baseline across conditions. Anticipated Incentives (AI) vs. Control (C). Standard error bars are shown.

We also analyze the effect of the COVID-19 pandemic on mobile usage at the end of the first RCT. We find that subjects increased their mobile usage considerably after the university was closed due to COVID-19. Although our subjects were very concerned (overall) about the COVID-19 pandemic, we find that subjects in the FI condition who reduced their smartphone usage were less concerned than subjects in the other conditions.

3.2 Follow-up RCT

The results of the follow-up RCT supplement findings from the first RCT. Subjects in the AI condition pre-emptively reduced their usage in period 1 (the incentive-pre-announced period) and maintained a lower usage than the C condition in period 2 (the actual incentivized period). Importantly, they were able to maintain a lower usage than the C condition during the post-treatment period (Figure 3).

We also measured subjects' belief about their period 2 target achievement both at the beginning and end of period 1. If subjects believe that their usage reduction in period 1 will enable them to achieve the target in period 2 more successfully, they should reduce their usage in period 1. We found this to be the case, by regressing the number of days target was achieved in period 1 on the belief (at the beginning of period 1) in target achievement in period 2. Together, the evidence points to a significant degree of rational addiction among our subjects.

In addition, similar to the first RCT, we also find that subjects with higher baseline usage (or higher absolute targets) reduced their usage more in period 1.

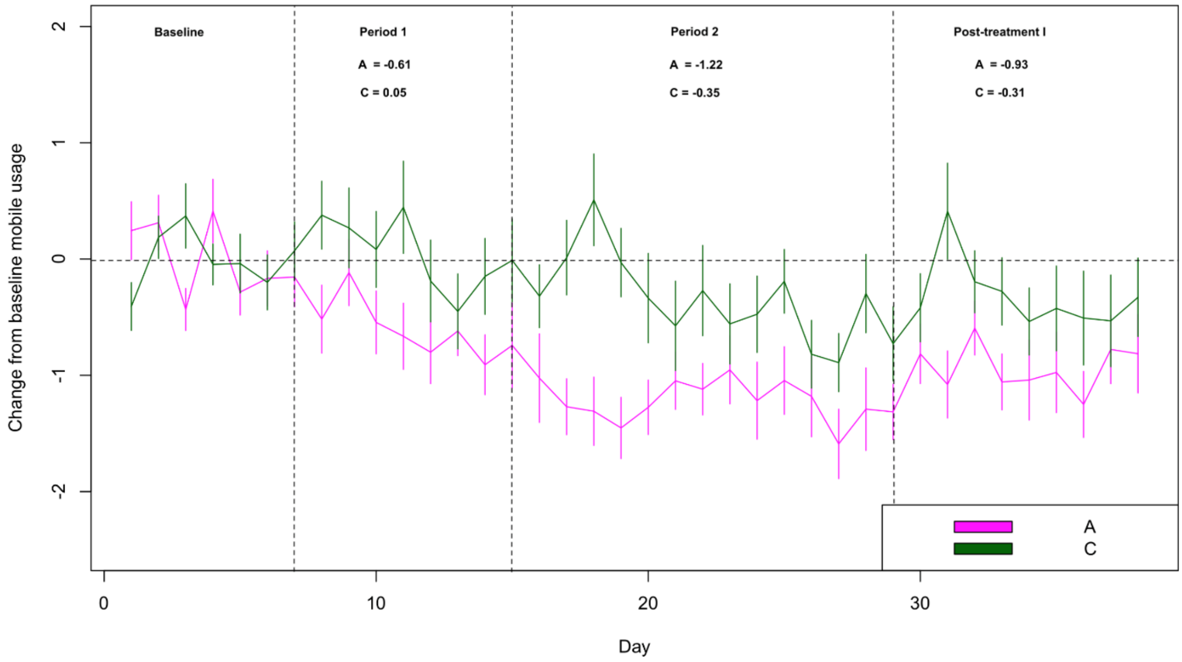

Figure 3. Follow-up RCT: Average daily change in mobile usage from baseline across conditions. Anticipated Incentives (AI) vs. Control (C). Standard error bars are shown.

3.3 Other self-reported outcomes

Subjects who achieved the target more frequently in period 1 and 2 in both RCTs reported lower (and a decrease in) nomophobia (i.e., anxiety of not having access to one's smartphone, *p*s < 0.05). We also measured time preferences and cognitive reflection before and after the treatment in our first RCT. However, we find no systematic differences. Similarly, we do not find any evidence for immediate causal benefits of reducing screen time in terms of self-reported measures of productivity, distractibility, procrastination, and self-control in either RCT.

4. Implications and discussion

Our RCTs provide an empirical demonstration of rational addiction. Compared to one previous RCT that investigates rational addiction in handwashing (Hussam, Rabbani, Reggiani, & Rigol, 2017), we are able to identify the subject group that responds to future incentives (in our case heavy mobile users). In addition, we are able to precisely estimate the effect of anticipated vis-à-vis actual incentives in inculcating and sustaining a behavioral change. For policy-makers, this is important because anticipation treatments could effectively support the most vulnerable (heavy) users at a lower cost.

Research in consumer psychology indicates that anticipation of a future behavior can lead to the opposite behavior pattern (Fishbach & Dhar 2005). Such 'anticipatory licensing effects' have been observed in the domain of dieting and exercise (e.g., the last supper effect; Urbszat, Herman, & Polivy 2002). In our case, the licensing literature would suggest the opposite to rational addiction—an increase of usage in period 1 in anticipation of a future reduction in period 2. With our RCTs, we are able to empirically rule out this alternative theoretical prediction.

While the majority of previous research on smartphone consumption used correlational data or imprecise self-reports (Kaye et al. 2020), we objectively measure individual-level mobile screen time with a novel methodological approach (using screen time apps). Additionally, compared to existing studies on social media consumption that incentivize complete abstinence or extremely low usage (e.g. Collis & Eggers, 2019; Allcott et al., 2020), we provide more realistic, sustainable targets (25-30% reduction).

With our first RCT we are able to study the sustenance of habits after an external, unforeseeable shock. The lockdown due to the COVID-19 pandemic increased the mobile usage of our subjects by ~37% (or 1.7 hours). Despite this shock, subjects in the FI condition were able to sustain a lower usage than the control condition.

Although subjects in the AI treatment had a lower usage in period 1 and in period 2, in our first RCT they were not able to sustain the lower usage in the post-treatment. One plausible explanation for this lack of 'habit stickiness' could be that the anticipation period did not result in sufficient accumulation of habit stock. Therefore, unlike in the FI condition, we did not observe a sustained post-treatment reduction (or strong habit formation), especially in light of the COVID-19 related surge in screen time. In our follow-up RCT, when we increased the target to 30% (to foster anticipation) and the duration of the incentive period to 14 days, we not only replicated the anticipatory usage reduction in period 1 but we also observed a sustained usage reduction for the entire post-treatment period. Thus, we argue that the size of the target and the length of the incentive period could be important for increasing the stickiness of habit in the AI condition. Future research should investigate how anticipation treatments can be adapted further to lead to even longer lasting change in behavior.

Even though we found some evidence from the first RCT that subjects who reduced their smartphone usage had higher academic performance post-treatment, we could not compare pre- versus post-treatment GPAs and rigorously test the effect of our treatments. This is because most subjects were in their first academic year. Having access to pre-treatment GPAs would have allowed us to determine if mobile usage reduction resulted in higher GPAs or if students with higher GPAs responded more strongly to our treatments.

Finally, while the vast majority of subjects only possessed one phone (92-96%), our experimental setting does not allow us to observe if people substitute their lower mobile usage by increasing the usage of other digital devices, such as tablets or laptops. Future research could help understand this substitution effect.

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