Correcting Behavioural Biases in Screen Time Use

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Abstract

This paper adds to the literature on experimental interventions that target smartphone use. I begin by developing a conceptual framework that models screen time consumption using reference-dependent preferences. I then test the model's predictions in an experiment examining the screen time habits of college students. Specifically, participants are asked to rank their current screen time habits relative to perceived peer behaviour, and I use a randomized treatment to correct the extent to which they may have misperceived their relative position. I find that individuals are *(i)* uninformed about the screen time habits of their peers, *(ii)* misperceive their relative position in the distribution, *(iii)* and on an average, the findings suggest correcting misperceptions through social comparisons reduces daily average screen time use. *(iv)* I also find suggestive evidence of a reduction in smartphone screen time being associated with an improvement in academic grades.

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Introduction

Advancements in smartphone and social media technology have revolutionized communication, work, and brought connectivity to our daily lives. However, the rise in smartphone use has raised concerns about excessive use despite the practical benefits of smartphones. According to a report by WEF2021, overall media consumption among adults in the United States increased by 20.2 % between 2011 and 2021. In a study conducted among college students, Voss2023 find that about 46 percent of participants reported spending more than 6 hours a day on screens during the pandemic, in comparison to about 31 percent before the pandemic. However, concerns remain about potential adverse effects on mental health, meaningful social engagement, and cognitive development.

Studies show that excessive smartphone use has been linked to neurological disorders such as carpal tunnel syndrome (Karaçorlu *et al.*, 2022; Shahrani and Shehri, 2021), poor sleep quality (Maurya *et al.*, 2022), cognitive problems including attention deficiency (Montagni *et al.*, 2016), stress and depressive symptomatology (Boers *et al.*, 2019; Harwood *et al.*, 2014). In a study of broadband internet and mental health, Golin2022 finds suggestive evidence of a widening of the gender gap in mental disorders. Upon looking at sub-facets of mental health, she finds broadband access leads to a worsening of socializing behaviour and ability to cope with emotional problems. In her memoir *Careless People*, former director of public policy at Meta (previously Facebook) Sarah Wynn-Williams claims Meta identified teenage girls who had deleted selfies on Facebook, Instagram, and WhatsApp and forwarded their data to companies who used the data to target the girls with beauty products. This practice aligns with broader concerns about how social media platforms use personal data to target users with ads that may reinforce negative self-perceptions. In a recent paper, Bursztyn2023 estimate the consumer surplus of two popular social media platforms (TikTok and Instagram). They highlight the possibility of product market traps, where large shares of consumers are trapped in an inefficient equilibrium (where the over-use the platforms and derive negative utility) and would prefer the product not to exist.

In light of these observations which suggest undesired overuse of smartphones, research emphasizing digital addiction has therefore arguably gained traction in recent times, with a particular emphasis on plausible ways to target and limit unproductive screen time use. As a particularly germane example of a research study, Allcott2022 develop an economic model of digital addiction pertinent to social-media use, and estimate it using a randomized experiment. They find that temporary incentives to reduce social media use have persistent effects. Similarly, Hoong2021 explores the effectiveness of adopting commitment devices such as turning on the *Screen Time* feature on iPhones, and finds evidence of partial naiveté as respondents significantly under-predict the time they spend on their phones.

This paper adds to the literature on interventions targeting screen time use. I explore smartphone use from the perspective of social comparisons and leverage plausible misperceptions in judging one's position (relative to their peers) as a behavioural nudge to target excessive smartphone use. As a society, we observe and are often influenced by (and emulate) the behaviour of those around us. In other words, we try to "keep up with the Joneses" by watching popular TV shows, reading bestsellers, or even following social media influencers. Societal behavioural patterns therefore act as a point of reference for our own behaviour, and influence our choices. However, the behaviour of others is not always tangible, especially when we think about smartphone use. This makes determining a "reference point" difficult, and consequently clouds our judgement about where we stand relative to the societal reference point.

While extensive empirical and experimental evidence supports reference dependence in consumer choices, debate persists on how the reference point is determined. Theoretical models often assume an exogenous reference point, arising from either internal habit formation, where utility depends on past consumption, or external habit formation, where utility reflects deviations from the societal reference point. In KoszegiRabin, the reference point is an agent's beliefs about their own future consumption (internal habit formation). In contrast to this, studies in network theory in determining choice structures such as Langtry2023 assume the reference point to instead be a weighted sum of other agents' consumption, where the weights capture the strength of social comparisons (external habit formation). Several notions such as salience have been explored as plausible determinants of the reference point (see DellaVigna (2007); Bhatia and Golman (2018) and Kıbrıs *et al.* (2021) for a more detailed discussion).

Given the role of peer influence in decision-making, it remains unclear how accurately individuals perceive others' consumption, particularly for less conspicuous goods like screen time. This study investigates students' beliefs about their peers' screen time use and examines responses to a pre-registered online experiment that corrects misperceptions through a randomized intervention. To the best of my knowledge, this is the first study to examine perceived peer behaviour related to screen time and to leverage social comparison as a tool for behavioural change.

Past research demonstrates that providing individuals with information about their behaviour relative to peers (i.e., social norm feedback) can induce significant changes across diverse domains. For instance, descriptive norm feedback has led to reductions in household energy consumption (Allcott, 2011; Allcott and Rogers, 2014; Ferraro *et al.*, 2011), while informing high-prescribing physicians that they exceeded peer antibiotic prescribing rates reduced unnecessary prescriptions (Hallsworth *et al.*, 2016). Similar norm-based interventions increased tax compliance (Hallsworth *et al.*, 2017) and improved student academic performance (Azmat and Iriberri, 2010). Indeed, large-scale social comparison experiments have shown that even subtle norm cues can shift behaviours at scale, as evidenced by a 61-million-person online study of political mobilization (Bond *et al.*, 2012) and field interventions highlighting changing norms of sustainability (Sparkman and Walton, 2017).

Building on this literature, the present study applies a comparatively standard informational intervention to a novel domain: smartphone screen time. While the effectiveness of social comparisons has been widely documented in fields such as energy conservation and health-related behaviours, less is known about whether these strategies can alter digital consumption patterns. This paper contributes by providing causal evidence that correcting misperceptions of peer screen time can reduce daily smartphone use and potentially improve academic outcomes, thus expanding the evidence base for social norm interventions into digital behaviour.

The findings of my study can be summarized as follows. I find that individuals tend to hold inaccurate beliefs about their peers' smartphone usage and misperceive their own standing in the distribution. The evidence further suggests that correcting misperceptions about relative screen time can reduce usage, although a larger sample might be necessary to robustly detect effects of this magnitude. Notably, this decrease is driven solely by behavioural incentives, as no financial rewards are offered for reducing screen use. Finally, there is suggestive evidence that lower smartphone usage may be associated with improved academic performance.

The rest of the paper is organized as follows. Section 1 introduces the conceptual framework that motivates the study, Section 2 presents the design of the randomized experiment, a description of the data and model-free results. Section 3 describes the methodology and estimating equations. Finally, Section 5 provides a discussion on the results of the study, and Section 7 concludes. The pre-analysis plan was made public on OSF on the 14^{th} of May, 2023; one day before the endline survey was sent out.

1 Conceptual Framework

This section introduces a model of reference-dependent decision-making, drawing on the frameworks of KoszegiRabin and JordiGaliKUJ. The model is extended to incorporate misperceived beliefs about peer behavior, which in turn shape individuals' perceived reference points. This extension motivates the design of the experimental intervention. The model's testable predictions are evaluated using data from a pre-registered online experiment, as outlined in Sections 2 and 3.

1.1 Misperceptions about the group average

There are n agents in the model. Following the framework in Langtry2023, I assume that all agents are embedded in a weighted and directed network G, represented as an $n \times n$ matrix. Each entry G_{ij} captures the strength of the directed link from agent i to agent j. The weights reflect the quality of information or familiarity that i has about j: smaller values of G_{ij} correspond to stronger social ties or greater familiarity (e.g., close friends or frequent interactions), while larger values indicate weaker ties or limited knowledge (e.g., acquaintances or strangers). By construction, $G_{ii} = 0$ for all i, reflecting the assumption that individuals observe their own behaviour without bias.

The conceptual framework assumes that agents operate in an environment characterized by information asymmetries. In particular, individuals cannot directly observe others' smartphone screen time consumption due to its intangible and private nature. As a result, each agent i forms beliefs about agent $j's$ consumption based on available information:

$$c_j^i = c_j + b_{ij}.$$

Here, c_j^i denotes agent i's belief about agent j's screen time consumption, c_j denotes j's actual screen time consumption, and b_{ij} captures the error or bias in i's perception about $j's$ consumption. The bias term b_{ij} is modelled as a function of the strength of the social tie between the two agents:

$$b_{ij} = \alpha_j \cdot g_{ij},$$

where $g_{ij} = \frac{G_{ij}}{\sum_j G_{ij}}$ reflects the normalized weight of the directed tie from i to j, and α_j is an integer that captures the magnitude of potential misperception about j's behaviour. This formulation implies that misperception increases with weaker network ties. This also captures a stylized fact from Yang2021 that misperceptions about others are widespread, asymmetric, and much larger when about out-group members.

Each agent i then chooses a level of screen time consumption $c_i \geq 0$ that maximizes their subjective utility, which depends on the perceived norm or reference point r_i. This reference point reflects the average perceived consumption of others in the network and is defined as:

$$r_i = \frac{1}{n} \sum_j c_j^i.$$

Substituting the belief formation equation $c_j^i = c_j + b_{ij}$, the perceived reference point can be expressed as:

$$\begin{aligned} r_i &= \frac{1}{n} \sum_j \left(c_j + \alpha_j \cdot \frac{G_{ij}}{\sum_j G_{ij}} \right) \\ &= \frac{1}{n} \sum_j c_j + \frac{1}{n} \sum_j \alpha_j \cdot \frac{G_{ij}}{\sum_j G_{ij}}. \end{aligned}$$

Or,

$$\underbrace{\tilde{E}(c)}_{\text{Perceived average}} = r_i = \underbrace{E(c)}_{\text{Actual average}} + \underbrace{\frac{1}{n} \sum_j \alpha_j \cdot \frac{G_{ij}}{\sum_j G_{ij}})}_{\text{Error term}}$$

This implies that the perceived group average $\tilde{E}(c)$ consists of two components: *(i)* the actual group average $E(c)$, and *(ii)* a non-zero bias term that arises from misperceptions shaped by the network structure and individual-specific weights.

This leads to a key testable implication: *Due to systematic misperceptions about others' behaviour, individuals may form biased beliefs about the group's average* *consumption. This implies,* $\tilde{E}(c) \neq E(c)$.

1.2 Self-perceived relative placement

With a slight abuse of notation, let $F(c_i)$ be agent $i's$ true position in the distribution of screen time use, and $\tilde{F}(c_i)$ is their belief about their position in the cumulative distribution.

In the case of a discrete random variable such as daily screen time use, the CDF is represented by a non-decreasing step function. Its inverse, the *generalized inverse distribution function*, is used to describe values x associated with given percentiles p, and is defined as:

$$F_X^{-1}(p) = \inf\{x : F_X(x) \geq p\}.$$

However, for the same value of screen time consumption x, an agent's perceived relative position in the distribution of screen time use is conditional upon their idiosyncratic beliefs about the distribution, implying it is associated with a different quantile value $\tilde{p}$ such that:

$$\tilde{F}^{-1}(\tilde{p}) = inf\{x : \tilde{F}(x) \geq \tilde{p}\}$$

An individual who has imperfect information about the true distribution $F(c)$ and misperceives it as $\tilde{F(c)}$ will therefore misconstrue their relative placement as $\tilde{p}$ instead of p for the same value of screen time consumption x. This leads us to the second testable prediction: *Agents misperceive their relative position in the distribution, implying* $F(c_i) \neq \tilde{F}(c_i)$.

1.3 Choices under reference dependent preferences

The framework builds upon the KoszegiRabin (henceforth KR) setting, where individuals are concerned not only with the utility they derive from consumption of a good, but also their utility relative to a reference level of consumption. Thus, the agent's overall utility from consuming a good k thus has two additively-separable components - the first component, "consumption utility", corresponds to the material payoff traditionally studied in economics, which is denoted by $m_k(c_k)$. The second component, "gain-loss utility", derives from comparing $m_k(c_k)$ to a reference level of utility $m_k(r_k)$. The utility associated with outcome c_k in this framework is given by:

$$u(c_k \mid r_k) = \underbrace{m_k(c_k)}_{\text{Consumption utility}} - \eta \underbrace{v(c_k \mid r_k)}_{\text{Gain-loss utility}}$$

where the parameter η governs the weight placed on gain-loss utility and captures sensitivity to reference-dependent deviations. From the previous section, the agent believes that consumption is distributed according to the CDF $F\tilde{(c)}$ with a mean value $\tilde{E}(c)$, implying that the reference point r_k is the agent's expectation of the average consumption, $\tilde{E}(c)$.

Applying the above-mentioned framework to the context where k represents screen time, consider a consumer's decision problem formalized as the maximization of the general form of the utility function described below:

$$u(c,r) = \begin{cases} m(c) - \theta\lambda v(m(c), m(r)) & \text{if } r < c \ , \\ m(c) - \theta v(m(r), m(c)) & \text{if } r \geq c. \end{cases}$$

Here, $u(c,r)$ indicates utility from screen time consumption c, and r denotes the perceived reference level. The consumption utility $m(c)$ exhibits diminishing marginal utility at any level of consumption, and the gain-loss utility v captures the disutility from deviations relative to the reference. The parameter $\theta\lambda$ governs loss-aversion when consumption exceeds the reference level, and θ when it falls short. I impose $\theta \in (0,1)$ and $\theta\lambda \in (0,1)$, allowing $\lambda > 1$ as long as the product remains below unity. In this setup, individuals consuming above the reference point experience losses from over-consumption manifesting as regret, wasted time, or fatigue such as eye-strain, weighted by $\theta\lambda$. Conversely, those below the reference experience disutility from under-consumption, potentially due to social disconnect or fear of missing out, weighted by θ. While no restriction is imposed on the relative size of these penalties, both are assumed to affect decision-making.

To illustrate, consider the following specific form:

$$u(c,r) = \begin{cases} c^{\frac{1}{2}} - \theta\lambda(c^{\frac{1}{2}} - r^{\frac{1}{2}})^2 & \text{if } r < c \ , \\ c^{\frac{1}{2}} - \theta(r^{\frac{1}{2}} - c^{\frac{1}{2}})^2 & \text{if } r \geq c. \end{cases}$$

In this example $m(c) = c^{\frac{1}{2}}$, which exhibits dimininishing marginal utility, and $v(m(c), m(r)) = (m(c) - m(r))^2$ is quadratic in utility deviations.

The first order condition of utility maximization allows us to find the optimal consumption of screen time, c^*, as a function of the parameters θ, λ and r, as explained in detail in the appendix. A simple comparative statics exercise illustrates that the optimal consumption level c^* moves in the direction of the reference point r, as indicated by $\frac{\delta c^*}{\delta r} > 0$. This implies changes in the reference point lead to corresponding adjustments in optimal consumption consistent with reference-dependent preferences.

This implies, when the perceived reference level is nudged by an amount δr, individuals respond by altering their choices to match the new reference point, and the optimal consumption moves in the direction of the perceived reference level by δc^* units. So if an experimenter were to hypothetically nudge an agent's misperceived relative position $\tilde{p}$ which is reflective of $\tilde{F(c)}$ and give them the true figure p, the agent receives a signal that they have formed incorrect beliefs ($\tilde{F(c)}$) about the true distribution, $F(c)$. The agent then updates their belief about the distribution and consequently its mean, which then acts as a new reference level on the basis of which they re-calibrate their consumption decisions.

This leads to our final testable prediction: *individuals adjust their consumption in response to signals that shift the perceived reference point. Specifically, optimal consumption* c^* *moves in the same direction as the reference level* r*, since* $\frac{\delta c^*}{\delta r} > 0$ *holds for both types.*

1.4 Testable predictions

Following the model's assumptions and results, we have the following testable predictions:

- Owing to their inaccurate beliefs about the distribution, individuals may have inaccurate perceptions about the group average, implying $\tilde{E}(c) \neq E(c)$.
- Agents misperceive their relative position in the distribution, implying $F(c_i) \neq \tilde{F}(c_i)$
- Individuals respond to signals indicating changes in the perceived reference point, as $\dfrac{\delta c^*}{\delta r} > 0$.

  Through the experiment, a treated individual who misperceives their relative position can receive either of the two signals, $s_x = \{o, u\}$ where they are informed that they either over-estimated or under-estimate their screen time use relative to other participants. Following upon the model's predictions, an individual who is treated ($T_i = 1$) and receives a signal indicating *Overestimation*

($D_i = 1$) would reduce their screen time use, and vice versa.

2 Experimental Design

The experiment was conducted between the first week of May 2023 and lasted until early June 2023 with university students as participants who were recruited through an online survey. The experiment evaluates the effect of an intervention that corrects misperceptions about how an individual's smartphone screen time usage compares against that of other participants. There are two stages, which are described in detail in Section 2.2. In the first stage, participants answer an online survey where their daily average screen time for the past week is recorded, and their subjective belief about where their screen time use ranks in comparison with other participants is elicited.

Participants who complete the first survey and meet certain requirements (described in details in the following sections) are then invited to participate to the second survey, where an equal number of participants are randomly assigned to either a treatment or a control group. Both groups receive an email thanking them for their participation and a reminder to fill out the next survey. In addition, participants assigned to the treatment group receive a signal quantifying the extent of their misperception in the same email. The second survey then records their daily average screen time for the week when the intervention was administered. Both the online surveys were designed using Qualtrics.

2.1 Participants

Students enrolled in the Bachelor's or Masters programs at a university in Sweden were invited to participate in a research study through an online survey. A link to the survey was circulated through email to almost all such students whose contact information was available on the school's homepage, and shared through QR codes to students present within the premises of the university. In classes with a batch size of 200 or more enrolled students, the QR code was projected during the break to maximize participation. Of those who started (but did not necessarily complete) the first survey, approximately 30.2% accessed it through an email link, and 69.7% through the QR code.

At the start of the baseline survey, participants are informed of the eligibility criteria: they must be enrolled in either a Bachelor's or Master's program and possess a valid student identification number (hereafter, Student ID). Participation requires students to provide their Student ID, which serves to uniquely identify individuals in the dataset. This identifier is used to link survey responses with administrative academic records (e.g., exam grades) and to enable email communication related to the study. Participants are required to give informed consent for the collection and analysis of their screen time data. They are clearly and truthfully informed that all data will be anonymized and used exclusively for research purposes.

In the experiment, 331 students registered for the first stage, of whom 272 met the eligibility criteria to be enrolled in the study. Participants were randomly assigned to treatment and control groups, with an equal allocation of 50% to each group. In the second stage, 73 participants dropped out, resulting in a final sample of 199 students who completed the full study.

2.2 Stages of the experiment

The study was carried out in two stages: the pre-intervention survey, and the post-intervention follow-up. A visual overview is presented through the Timeline.

Baseline period: This period represents participants' natural screen time behaviour prior to the study. No survey was administered during this time. Participants later self-report their average daily smartphone screen time for this period, providing a measure of baseline usage.

Pre-intervention: During this stage, students complete an online survey where they report their average daily screen time during the baseline week. This retrospective measurement offers a modest advantage over app-based tracking, which may prompt behavioural changes once monitoring begins and the design thus helps to reduce potential Hawthorne effects.

The survey questionnaire also elicits their perceptions about where they think they lie in the distribution of screen-time, in comparison to their peers. This is done by eliciting their perceived percentile score, between 1 to 99. *Thus, for each participant, we have a self-reported perceived percentile score, based on their reported screen time use in the baseline period.*

Along with this, I also elicit a modified scale of their subjective smartphone dependence score (adapted mostly from the psychology literature following Roberts *et al.* (2015); Allcott *et al.* (2022)), how much time they think other participants spend on their phone, and their characterization of too much screen time. The survey also elicits answers to certain demographic questions such as their gender, for a comprehensive list of all such variables used in the study, please refer to Table 1.

Participants proceed to the next stages of the study upon meeting certain eligibility criteria. Students who do not provide any past screen time data or enter 0 are excluded from the analysis. Participants who answer a baseline daily average screen time use above 24 hours are considered to have misreported by accidentally sharing the total weekly (instead of daily) screen time use, and this is corrected. Misreported student IDs are corrected for such that the final list only includes students who provide valid identification. Individuals who report their daily screen time above 1000 minutes (16.67 hours) are excluded from the study owing to possible contentious misreporting, assuming individuals need $6 - 8$ hours of time on self care and sleep, daily.[1] While designing the survey, the feature "force response" on Qualtrics was used such that the respondent is unable to proceed along the survey without answering the compulsory sections, to avoid potential missing values.

At the end of the survey, eligible participants are randomly assigned to either the treatment or control group, with 50% in each.

Intervention: The intervention happens on May 10^{th}, and constitutes sending a signal to the treatment group, indicating their relative misperception through social comparisons.

- The control group receives an email thanking them for participating, and requesting their participation in the post-intervention survey.
- The treatment group receives an email that provides them with a signal of the extent of their subjective misperception. For example, a student who has answered that they believe their percentile score is 50, and is actually in the 75^{th} percentile is informed that in the survey, *you answered that you believe your percentile score was* 50*, but* when we compared your screen time to that of other participants *you actually belonged to the* 75^{th} *percentile,* meaning 75% of other participants use less screen time compared to you and 25% use more screen time.

Informing participants of their subjective misperception implies little risk of

[1] In the pre-analysis plan, I mistakenly wrote 18 hours and not 16.67 hours

contamination, as such information is strictly exclusive and only pertinent to the person receiving the email, and cannot be easily communicated to those in the control group. Regardless of treatment assignment, those in the treatment and control groups receive an equal number of emails.

Post-intervention period: Data collection for the post-intervention survey starts on 15^{th} May, 2023. The second survey elicits participants' daily average screen time use post intervention. In addition to this, I also elicit their daily screen time goal, and the division of time between the categories *Productivity and Finance, Creative, Social* and *Games.* Final grade data becomes available in August, and academic outcomes (exam grades) are later obtained and linked to participants' responses using the Student ID.

Timeline 1: *A brief overview of the timeline*

May $1^{st} - 6^{th}$ — **Baseline period**

May $8^{th} - 10^{th}$ — **Pre-intervention**

Elicit perceptions on:

Ideal smartphone use, peer behaviour, relative rank, smartphone dependence.

Record screentime use for the baseline period

Participants are randomly divided into *Treatment* and *Control*

May 10^{th} — **Intervention**

Control and *Treatment* are both thanked for their participation.

Treatment is also informed of their subjective misperception.

May 15^{th-} — **Post - intervention**

Data collection & payment

May 18^{th-} — **End of semester examinations**

Aug 14^{th-} — **Obtaining participants' grades**

Grades are linked with participants' survey answers

Writing and analysis

2.3 Measuring smartphone screen time use

Smartphone screen time is measured using the built-in application *"Digital Wellbeing"* for smartphones with an Android operating system, and its counterpart *"iOS Screen Time"* for Apple's iPhones. Both of these are inbuilt features of a smartphone, which constantly operate in the background to track which applications are being used on the phone, and for how long. Primarily, they provide an overview of one's screen time consumption for up to the past twenty eight days (four weeks) from the current day, thus enabling participants to share their daily average screen time for a particular week. [2]

While both measure screen time use, there have distinctive features which are unique to the version and operating system of the smartphone. *"Digital Wellbeing"* displays screen time use as a pie chart, graphically illustrating the time spent on each app as a part of the total time spent. In addition, it also displays the total number of times the phone was unlocked, notifications received and ways to disconnect. For iPhones, the same data is displayed as a bar graph, with their own classification of applications within the categories social, creativity, finance, or games (these categories vary across models and languages). It displays the most used applications, and categories. While both operating systems allow one to go back and forth across dates, iPhones generally present an immediate comparison of how the current week's daily average screen time compares against the past week's average, and also allows it to be displayed as notification, meaning, the screen time use of the current date is presented at a glance upon unlocking the phone. This implies, iPhone users may be more rationally attentive towards their phones than other variants where this feature is not immediately available, we therefore control for the operating system, and also for whether the participant uses an app to monitor or limit screen time.

[2]While iPhones generally display weekly data automatically, this feature may not be available for all Android phones, they manually enter the data for each day of the week, and the daily average for the week is then manually calculated.Participants are automatically directed to a part of the survey which provides clear instructions on how to access these sections on their phone, upon selecting the set-up that is most relevant to them.

2.4 Data and construction of Variables

Screen time use: This section provides an overview of the data used for estimating the specifications described further in Section 3. The following table presents a list of the demographic variables that are included as covariates in the analysis.

Table 1: Factors affecting screen time use

Variables	Description
Gender	A dummy variable indicating gender.
Commute	Indicator variables for duration of commute from home to school. This ranges between: "*less than 10 minutes*" "*10 - 19 minutes*", "*20 - 29 minutes*", "*30 minutes - 1 hour*" to "*more than one hour*".
Software	Indicator variables for the phone's operating system, "*Android*" "*iPhone*" and "*Other*".
Monitoring	Indicator for whether the respondent uses an application to monitor screen time.
Partner	Having a geographically distant partner dependent on virtual connection.
Program	Categorical variables indicating course specializations across programs: *BSc Business and Economics*,*BSc Retail Management*, *MSc International Business*, *MSc Finance*, *MSc Accounting Valuation and Financial Management*, *MBM Business Management*, *MSc Economics*
Year	Categorical variable indicating the year of enrollment in the program.
Enrollment	Whether the student is currently enrolled in a course at the University.

Notes: The table provides a description of the covariates that are controlled for in the experiment.

I compute a measure of attachment to one's smartphone from a battery of questions on a 7 point likert scale. Plausible answers range across a seven-point scale from "*strongly agree*" through "*neither agree nor disagree*" to "*strongly disagree*," which were coded as -1, -2/3, -1/3, 0, 1/3, 2/3, and 1, respectively. *"Smartphone Dependence Score"* is the sum of these numerical scores for the seven questions, such that more positive scores reflect lesser subjective attachment to one's smartphone.

Lastly, even though the experiment relies upon data pertaining to screen time use, this measure has its own limitations. An individual's screen time use may be an outcome of several factors, some of which (such as the presence of applications that monitor screen time) are more tangible and can be accounted or controlled for. However, it is also likely to be influenced by other factors such as eyesight, personality, social connections and mental health which are difficult to measure and account for.

Further, the built-in screen time feature tracks time spent on applications with the screen active, which may not always reflect actual phone usage. For instance, listening to a podcast on *YouTube* contributes to screen time, whereas listening to the same podcast on *Spotify* with the screen turned off does not—even though both activities engage the user's attention for the same duration.

Academic achievements : This section provides an overview of the data on academic achievements as received from the institution where the students are enrolled, that is used for estimating the empirical specifications outlined in Section 3.

Table 2: Grades

Variables	Description
Registration number	The student's registration number in the university's record.
Course Number	A unique number assigned to each course at the institution.
Credits	The ECTS credits for the corresponding course number.
Date of Grade	The date when the grade was reported
Grades	Grading scale: Excellent, Very Good, Good and Pass
Comment	Indicates courses where the highest possible grade is pass.

Notes: The table outlines the variables relevant to participants' academic achievements.

The variable *Date of Grade* enables the construction of the variable *Quarter*, which allows one to understand whether the course grades were obtained in an examination prior to or post the intervention.

Certain courses can only award a pass, as indicated by the variable *Comment*: these are excluded from the analysis, as there is limited scope of the grade being reflective of merit. Some grades are marked as $Transfer$ or *Exchange* indicating credits from a partner university that have been transferred to the participating student's university, but that the grades have not been converted. These are also excluded from the analysis owing to concerns about differences in the grading scale. In addition, $Fail$ is not a formal grade at the institution; a student can register for a course multiple times without achieving a grade but such registrations are not included in their *Transcript of Academic Records* or *Grade Point Average* until they receive a final grade in the course. For each *Quarter*, the Grade Point Average GPA is calculated in the following manner, where the calculation is performed by assigning a numerical value to each grade *(Excellent = 5.00 points, Very Good = 4.00, Good = 3.50, Pass = 3.00)*:

$$GPA = \frac{\sum(\text{Grade number} * ECTS\ credits)}{\sum(ECTS\ credits)}$$

2.5 Payment

Payment happens through a lottery, where participants win gift cards worth 1500 SEK from a popular grocery store chain in Sweden. One out of every thirty participant wins the prize, conditional upon providing digital proof that their survey answers match the data entered from their smart phone. The prizes are determined in a random draw, and the winners are contacted personally through their university email address linked to their Student ID.

First, this incentivizes participants to be truthful and meticulous with reporting the data, as they are informed beforehand that they may only win a prize upon showing proof that their answers are credible. Second, in comparison to recent experiments that provide monetary incentives to limit digital addiction or screen time use, here participants have no direct remunerative incentives to reduce screen time, and thus any observed outcome is reflective of their response towards the behavioural intervention only, and arguably unconfounded from any income effect.

3 Balance of Covariates

Table 3 presents the balance of baseline covariates between the treatment and control groups. This demonstrates that randomization produced comparable groups in terms of observed characteristics. All pre-specified baseline covariates (including commute time and enrollment status, which exhibit some imbalance) are included as control variables in the estimated specifications. Controlling for these covariates ensures that estimated treatment effects are not confounded by observable differences between treatment and control groups, thereby improving the precision and validity of the estimates.

Table 3: Balance of covariates

Variable	(1) Control (0) Mean/(SE)	(2) Treatment (1) Mean/(SE)	(1)-(2) Mean difference
Baseline screentime	255.851	270.698	-14.846
	(11.760)	(12.687)	
Gender	1.531	1.524	0.007
	(0.051)	(0.049)	
Commute	2.125	2.592	-0.467***
	(0.119)	(0.111)	
Software	1.854	1.845	0.010
	(0.036)	(0.036)	
Monitoring	1.750	1.757	-0.007
	(0.044)	(0.042)	
Partner	1.198	1.243	-0.045
	(0.041)	(0.042)	
Program	3.115	2.806	0.309
	(0.241)	(0.225)	
Year	1.698	1.748	-0.050
	(0.074)	(0.078)	
Enrollment	1.948	2.000	-0.052**
	(0.023)	(0.000)	
Smartphone dependence score	-3.202	-3.354	0.151
	(0.119)	(0.132)	
Observations	96	103	

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The table presents the balance of covariates.

4 Testing for Attrition

Following the planned implementation, there are two rounds of the survey which requires completion for a respondent's participation to be considered fulfilled. Therefore, attrition or non-response becomes an important consideration for the research study as it acts as a threat to internal validity. In order to limit attrition, I sent out reminders to all those who completed the first survey but failed to answer the second survey.

In the study, treatment assignment is completely randomized, and our identification rests on the assumption that respondents in the control group are a good counterfactual for those assigned to treatment, at follow-up. Therefore, it becomes important for us to test for differential attrition rates to determine if there are systematic differences in attrition rates between those assigned to control and treatment groups respectively, following Ghanem2021. This is done by regressing the variable $Attrition_i$, (which takes the value 1 if individual i answers the second survey, and 0 otherwise) on the treatment indicator T_i and previously specified covariates following the main analysis. The results are presented in Table 4. We see that the coefficient on treatment is close to 0 and insignificant, indicating that the study does not suffer from the problem of selective attrition.[3]

5 Estimation and Results

Following the conceptual framework in Section 1, I first test whether individuals accurately perceive their relative placement among peers. If individuals form inaccurate beliefs about the distribution, that is, $\tilde{F}(c) \neq F(c)$, they are likely to misperceive their relative rank among peers. I test this in the experiment by comparing participants' self-reported perceived ranking with their actual rank among their peers, through a paired t-test.

The results of the experiment corroborate the above conjectures. I find that on average individuals hold inaccurate beliefs about peer behaviour as reflected by their perceptions about the the group average - participants perceive the average daily screen time use of their peers to be 284.2 minutes, while the actual average baseline screen time use is 263.5 minutes. The difference of 20.62 minutes is significant ($p < 0.01$).

The second hypothesis from the conceptual framework examines whether agents form inaccurate perceptions about the group average, that is, $\tilde{E}(c) \neq E(c)$. I test this in the experiment by comparing participants' self-reported belief about how much time they think other participants spend on their smartphone on a daily basis, against the actual average daily baseline screen time for the sample, through an unpaired t-test. I find that participants significantly misperceive their relative position in the distribution, the difference between the actual and perceived percentile is 7.226 units, and this difference is significant ($p < 0.05$). This suggests individuals think others spend more time on their phones on an average, as the perceived daily average screen time is significantly higher than the actual.

[3] In the pre-analysis plan, I wrote : "for examinations where the student fails to achieve the passing grade, such grades may not be registered leading to a difference in the number of passed courses between those in the treatment and control group, and we also test for such differences." However, as there are no fail grades in the system, this is no longer relevant.

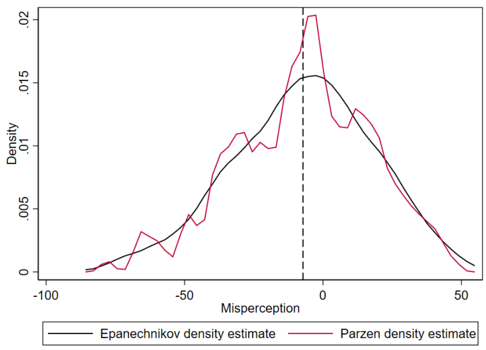
Table 4: Attrition

Variables	Coefficient	SE
Treatment	0.0220	0.0551
Baseline screen time	0.000420*	0.000241
Gender: Male	0.0639	0.0557
Commute:		
20–29 minutes	0.0699	0.0693
30 minutes – 1 hour	-0.0333	0.0838
Less than 10 minutes	0.0543	0.0786
More than 1 hour	-0.446***	0.152
Software: iOS	-0.0975	0.0764
Monitoring: Yes	0.0815	0.0634
Partner: Yes	-0.159**	0.0677
Program:		
BSc Retail Management	0.364***	0.0571
MBM Business and Management	0.132	0.106
MSc Accounting Valuation and Financial Management	0.196*	0.114
MSc Economics	0.366***	0.0640
MSc Finance	0.167*	0.0920
MSc International Business	0.196**	0.0903
Year:		
Second Year	0.0184	0.0607
Third Year	0.0992	0.0820
Enrollment: Yes	0.00106	0.167
Smartphone dependence score	0.0189	0.0211
Constant	0.578***	0.217
Observations	272	

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The outcome variable is an attrition indicator equal to 1 if the participant did not complete the post-treatment survey, and 0 otherwise. This specification includes the full set of baseline covariates. Robust standard errors are reported in parentheses.

In the experiment, the perceived reference point is nudged through a randomized experimental intervention where those in the treatment group are informed of the extent of their relative misperception. In order to identify the causal effect of the treatment, the following specification is estimated to understand how the intervention affects participants' screen time use in response to the randomized

Figure 1: Distribution of Misperception



Kernel density plots of the misperception distribution, defined as the difference between individuals' actual and perceived percentiles in the screen time distribution. Values to the left indicate underestimation of one's rank; values to the right indicate overestimation. The two kernel types shown are Epanechnikov and Parzen.

information treatment:

$$Screentime_i = \alpha_0 + \alpha_1 T_i + \alpha_2 X_i + e_i. \tag{1}$$

$Screentime_i$ refers to individual i's daily average screen time consumption (in minutes) post intervention, and T_i refers to treatment assignment. In all specifications, I control for an individual's baseline screen time use along with a vector of covariates (X_i) as specified previously. The coefficient of interest, α_1 is the change (in minutes) in an individual's screen time as a result of the intervention. If the estimated effect is negative, it is indicative of the intervention reducing screen time consumption. The results are presented in Table 5, and I find that the intervention reduces daily average screen time use by 15.05 minutes, which corresponds to about 5.7% of baseline use and a standardized effect size of 0.12. The outcome is comparable to the results of the bonus treatment in Allcott2022 where participants reduce their daily average use by over 20 minutes under a treatment where individuals receive \$50 (with a maximum possible earning of \$150) for every hour of reduced average daily FITSBY screen time below a bonus benchmark. However, it becomes germane to note that in my experimental setup, participants have no direct remunerative incentives to reduce screen time as the intent was learning about peer behaviour. Thus, the observed reduction is reflective of their response towards the behavioural intervention alone, and is arguably unconfounded from any income effect. As robust errors may be unreliable in small samples, I also compute permutation-based p-values based on $1,000$ random reassignments of the treatment indicator based on the main specification. These values closely match the analytical p-values confirming the robustness of the results.

Table 5: Effect of the treatment on screen time reduction

Variable	(1)	(2)
Treatment	-15.85*	-15.05*
	(8.655)	(8.791)
Baseline screen time	0.839***	0.827***
	(0.0503)	(0.0513)
Gender: Male		6.390
		(8.874)
Commute:		
20-29 minutes		-21.52*
		(12.04)
30 minutes - 1 hour		0.121
		(13.47)
Less than 10 minutes		-10.51
		(13.18)
More than 1 hour		-42.46**
		(17.32)
Software:iOS		9.661
		(11.37)
Monitoring: Yes		6.076
		(10.89)
Partner: Yes		-13.07
		(10.45)
Program:		
BSc Retail Management		4.428
		(20.51)
MBM Business and Management		-12.79
		(12.94)
MSc Accounting Valuation and Financial Managment		0.171
		(15.77)
MSc Economics		-24.28
		(19.28)
MSc Finance		27.13
		(18.37)
MSc International Business		17.56
		(15.20)
Year:		
Second Year		-13.97
		(9.910)
Third Year		-12.47
		(13.61)
Enrollment: Yes		39.31*
		(20.80)
Smartphone dependence score		-2.058
		(3.128)
Constant	50.24***	7.592
	(12.34)	(30.74)

Notes: *** p<0.01, ** p<0.05, * p<0.1. The outcome variable is average daily screen time use after the intervention, for 199 participants. Robust standard errors are reported in parentheses.

I next estimate the following specification, which is central to the analysis:

$$Screentime_i = \alpha_0 + \beta T_i \cdot D_i + \delta_1 T_i + \delta_2 D_i + \gamma X_i + e_i. \tag{2}$$

In the above specification, $D_i > 0$ when the actual percentile of individual i's screen time use is higher than their perceived percentile score. This implies, the treated individual i learns the following: in comparison to their peers, their screen time use is higher than how they perceived themselves to be placed. For simplicity, I refer to this as receiving a signal indicating *"overestimation"*. The coefficient of interest here is β. A negative value indicates that those that were treated ($T_i = 1$) and receive the signal $s_x = o$ for *"overestimation"* ($D_i = 1$) reduce their screen time use, in alignment with the conceptual framework outlined in Section 1.

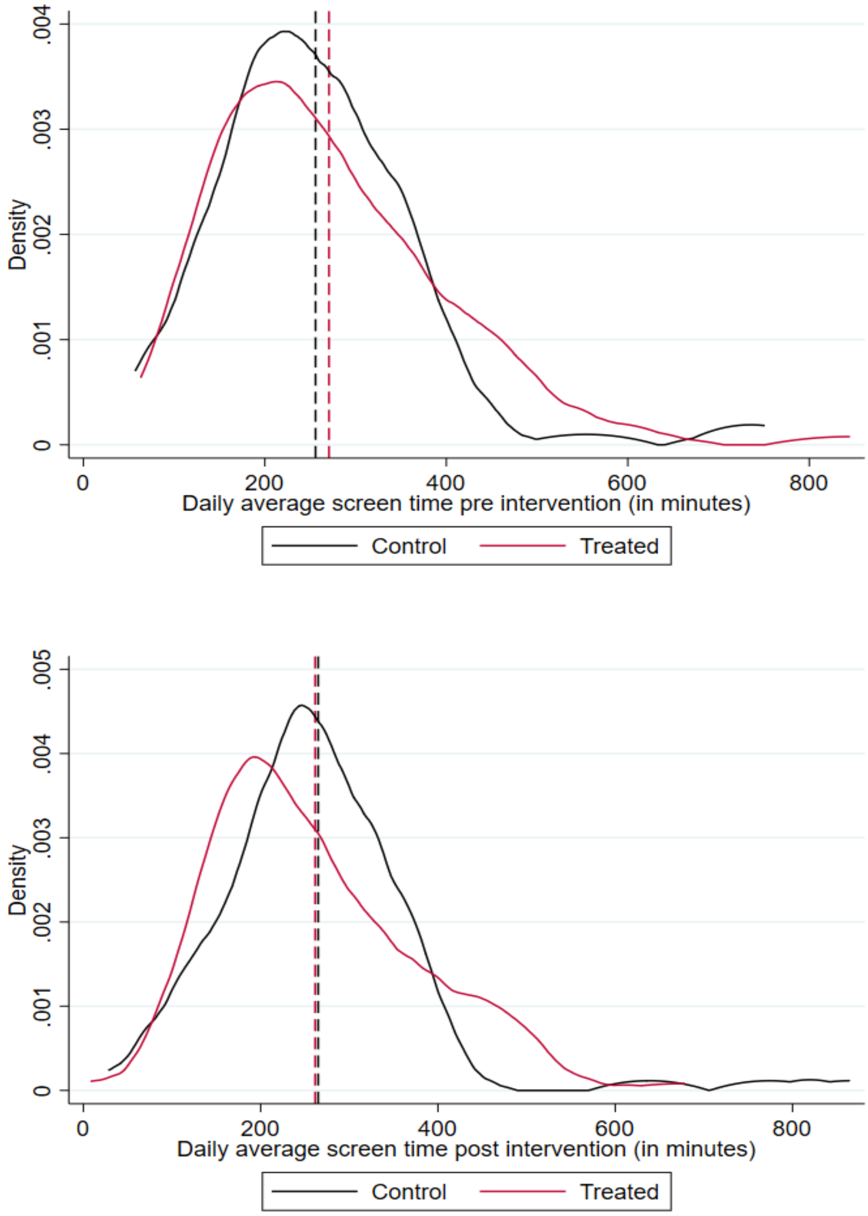
Table 6 presents the results of estimating equation 2. The results indicate that among the treated participants, those who are informed they have been overestimating their relative position ($T_i D_i = 1$) appropriately respond by reducing their screen time consumption post intervention relative to their baseline behaviour (however, these results are not significant) as evidenced by the negative β coefficient from Table 6 - their daily average screen time falls by 22.19 minutes from the baseline. This too is in line with the third testable prediction outlined in Section 1, i.e, individuals move in the direction of the nudge in their reference point. The results are graphically described below in Figure 3. The figure displays the mean and 95% confidence interval of the change in screen time, comparing treated and control groups relative to baseline levels, disaggregated by the degree of overestimation. The results show that, relative to baseline usage, individuals who initially overestimated their screen time rank tend to reduce their usage following the intervention.

Table 6: Interaction between misperception, treatment and screen time reduction

Variables	Coefficient
Treatment	-5.509
	(11.01)
Misperception Indicator (D_i) = 1	-11.26
	(13.29)
Treatment (T_i) * Misperception Indicator (D_i)	-22.19
	(21.70)
Gender	Yes
Commute	Yes
Software	Yes
Monitoring	Yes
Partner	Yes
Program	Yes
Year of study	Yes
Smartphone dependence score	Yes
Observations	199

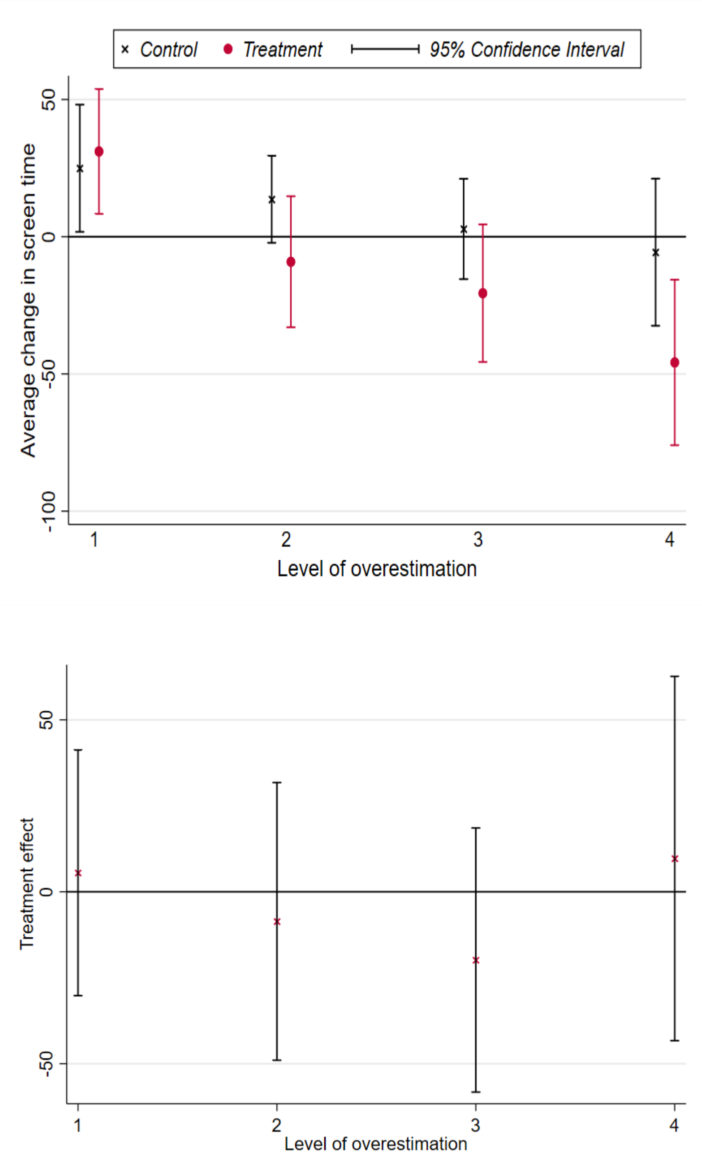
Notes: *** p<0.01, ** p<0.05, * p<0.1. The outcome variable is average daily screen time use after the intervention, for 199 participants. In this estimation, the main specification is estimated along with the full set of controls, additionally including an indicator for Misperception, D_i and its interaction with the Treatment indicator, T_i. Robust standard errors are reported in parentheses.

Figure 2: Kernel Density plots



The kernel density plots illustrate the distribution of screen time use pre and post intervention for the Control and Treatment groups. The average screen time use for the treated group falls post intervention in comparison to the baseline average.

Figure 3: Average difference in screen time use by level of overestimation



The figure plots the mean and confidence interval for the average difference in screen time use between the treated and control group in comparison to the baseline average, by level of overestimation. On the left are participants who underestimate their relative position, i.e., compared to others, they use less screen time than they thought while on the right are individuals who overestimate their screen time use. Compared to baseline usage, the ones on the left (right) increase (reduce) their screen time use.

To test whether individuals converge toward the group median after the intervention, I estimate the following specification, following standard models of belief updating in the KUJ framework. Specifically, I assess whether participants who are above or below the median level of misperception differentially adjust their behaviour in response :

$$|y_{i,t} - y_{t-1}^m| = \alpha_0 + \beta T_i + \gamma X_i + \delta Z_i + e_i. \tag{3}$$

Here, $|y_{i,t} - y_{t-1}^m|$ denotes the absolute deviation of individual i's post-intervention screen time ($y_{i,t}$) from the baseline median screen time (y_{t-1}^m). T_i is an indicator for treatment assignment, and X_i is a vector of baseline covariates. The variable Z_i is an indicator equal to 1 if individual i's misperception is above the sample median, and 0 otherwise. Misperception is defined as the difference between a respondent's self-reported perceived percentile rank and their actual rank in the baseline distribution.Thus, $Z_i = 1$ identifies individuals who overestimated their relative standing, while $Z_i = 0$ includes those who underestimated it, relative to the sample median.

The coefficient of interest δ, captures whether individuals with greater upward misperceptions exhibit different convergence behaviour relative to those with lower misperceptions. A negative and statistically significant δ would suggest that individuals who initially overestimated their standing tend to reduce their deviation from the group median post-intervention, which is consistent with directional learning or belief updating in response to norm-based information. Conversely, a null or positive δ would imply weaker or asymmetric adjustment among those with higher misperceptions. However, since Z_i is not randomly assigned, this analysis does not support a causal interpretation and the results should be viewed as descriptive evidence of behavioural responses that correlate with baseline misperceptions.

Table 7 presents the results from estimating Equation 3. The coefficient on the misperception indicator Z_i is negative and statistically significant ($\delta = -34.15$, $p = 0.006$), indicating that individuals who initially overestimated their relative screen time usage (i.e., those above the median misperception score) reduced their deviation from the baseline median more than those who underestimated it. This finding is consistent with models of directional learning or belief updating in response to normative feedback; individuals who learned they were not as excessive as they believed were more likely to adjust their behaviour toward the perceived norm.

Table 7: Convergence to the baseline median and misperception score

Variables	Coefficient
Treatment	6.039
	(10.13)
Misperception above median indicator $(Z_i) = 1$	-34.15***
	(12.28)
Gender	Yes
Commute	Yes
Software	Yes
Monitoring	Yes
Partner	Yes
Program	Yes
Year of study	Yes
Enrollment	Yes
Smartphone dependence score	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.1. The outcome variable is the absolute deviation of an individual's post-intervention screen time from the baseline median. This specification includes the full set of baseline controls, along with an indicator for whether an individual's misperception score is above the sample median (Z_i). Robust standard errors are reported in parentheses.

Finally, I examine whether reducing screen time has an effect on students' academic performance. To do this, I estimate the relationship between screen time and end-of-semester grades using an instrumental variables (IV) approach, in which post-intervention screen time is instrumented with treatment assignment.

As a first step, I estimate the reduced-form effect of the treatment on academic outcomes using the following specification:[4]

$$Grades_i = \beta_0 + \beta_1 T_i + \beta_2 X_i + \eta_i. \tag{4}$$

Here, $Grades_i$ denotes individual i's grade point average (GPA) for the end-of-semester examinations, conducted the week following the intervention. T_i is the treatment indicator, and X_i includes a set of pre-treatment covariates, including prior academic performance. Although the intervention period is relatively short, it directly precedes the exam period. If the treatment leads to a reduction in screen time and students reallocate that time toward studying, we may expect improvements in academic performance. The estimates in Table 8 show no statistically significant effect of the treatment on students' end-of-semester GPA, the coefficient on the treatment variable is small (0.034) and statistically insignificant. These

[4]As per the pre-analysis plan, I initially indicated that this regression would be estimated only if the t-statistic on T_i reached significance at the 5% level. Although the effect is significant only at the 10% level, I proceed with the analysis for completeness.

results indicate that the intervention did not produce measurable improvements in academic performance over the short time window between the treatment and the final exams.

Table 8: Reduced form effect

Variables	Coefficient
Treatment	0.0341
	(0.0832)
Baseline CGPA	0.490***
	(0.0681)
Baseline screen time	0.00033
	(0.00034)
Gender	Yes
Commute	Yes
Smartphone brand	Yes
Monitoring software	Yes
Long-distance partner	Yes
Program	Yes
Year of study	Yes
Enrollment at SSE	Yes
SAC	0.0357
	(0.0331)
Constant	1.771***
	(0.418)
Observations	164

Notes: *** p<0.01, ** p<0.05, * p<0.1. The outcome variable is the grade point average (GPA) for the end-of-semester exams. This specification includes the full set of baseline controls, and robust standard errors are reported in parentheses.

I also estimate the causal effect of screen time on grades using an instrumental variables (IV) strategy. Specifically, I instrument post-intervention screen time with treatment assignment, T_i. The first estimates the effect of treatment on screen time:

$$Screentime_i = \alpha_0 + \alpha_1 T_i + \alpha_2 X_i + \eta_i.$$

The second stage uses predicted screen time to estimate the effect on academic performance:

$$Grades_i = \beta_0 + \beta_1 \hat{Screentime_i} + \beta_2 X_i + \eta_i. \quad (5)$$

Here, $\hat{Screentime_i}$ represents predicted screen time from the first-stage regression, where actual screen time is regressed on T_i and controls. The coefficient of interest is β_1, which captures the causal effect of screen time on academic performance for students whose screen time was affected by the treatment. Under standard assumptions, β_1 identifies the Local Average Treatment Effect (LATE) —

that is, the causal effect of screen time on grades for the subset of students whose screen time behaviour was influenced by the treatment.

I find that a one-minute reduction in average daily screen time is associated with a 0.00352-unit increase in GPA. Scaling this to a more interpretable metric, a 30-minute reduction corresponds to an estimated increase of approximately 0.106 in GPA. Given the GPA is measured on a 5-point scale where a shift from "Pass" to "Good" corresponds to a 0.5-point change, this effect size represents roughly one-fifth of a letter-grade improvement. However, this estimate is not statistically significant ($p = 0.669$), and the confidence interval is wide. Therefore, the sign and magnitude of the coefficient should be interpreted with caution. The full results are presented in Table 9.

Table 9: The effect of screen time reduction on grades

Variables	Coefficient
$\widehat{\text{Screentime}}$	-0.00352
	(0.00824)
Baseline CGPA	0.446***
	(0.126)
Baseline screen time	0.00304
	(0.00633)
Gender	Yes
Commute	Yes
Software	Yes
Monitoring	Yes
Partner	Yes
Program	Yes
Year of study	Yes
Enrollment	Yes
Smartphone dependence score	Yes
Constant	1.862***
	(0.584)
Observations	164

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The dependent variable is the grade point average (GPA) for end-of-semester exams. This table presents the second-stage IV estimate, where predicted screen time ($\widehat{\text{Screentime}}$) is instrumented using treatment assignment. All models include the full set of covariates. Robust standard errors are reported in parentheses.

6 Heterogeneous Treatment Effects

The study also investigates whether the treatment effects vary across subgroups defined by individual characteristics such as gender, commute time, device software, use of screen monitoring apps, relationship status, academic program, year of study, and enrollment status. These analyses test for treatment-effect heterogeneity using interaction terms between treatment assignment and each subgroup indicator, as shown in Equation 2. The coefficient of interest is the interaction term, which captures whether the treatment effect differs for members of a specific subgroup. For example, one might expect that individuals who use screen monitoring applications (a proxy for greater awareness or self-regulation) might respond differently to the treatment.

However, I find no statistically significant or robust evidence of heterogeneous treatment effects across any of the subgroups considered. Interaction terms between treatment and subgroup indicators are consistently small and statistically insignificant across specifications. For instance, the interaction between treatment and monitoring app usage is negative (suggesting a larger reduction in screen time for monitoring users), but is far from statistically significant ($p = 0.876$). Similarly, no meaningful heterogeneity is observed by gender, commute time, or academic program. These results suggest that the treatment had a broadly similar effect across different participant characteristics. Full regression results are presented in in the Appendix.

7 Conclusion

Smartphone use has been on the rise, and research focusing on targeting unproductive screen time use has gained traction in recent years; considering the evidence suggesting that digital technologies are addictive and can have potentially adverse effects upon prolonged exposure. This paper attempts to add to the extant literature on experimental interventions that target excessive smartphone use.

Through a conceptual framework, I first explore the consumption of screen time through the lens of reference dependent preferences, where an individual's consumption decisions are affected by the perceived reference point which in turn is influenced by peer behaviour. I extend this theory to the consumption of screen time use and argue that for such choices where peer behaviour is less tangible, it becomes difficult to determine a reference point. This further precludes individuals from ascertaining how their consumption compares against peers, implying there may be a scope for misperceptions. Using a pre-registered online experiment, I study how individuals respond to a randomized intervention where such misperceptions are corrected.

I find that individuals form inaccurate beliefs about the screen time habits of their peers. They also misperceive their relative position in the distribution, and on an average, correcting misperceptions through social comparisons reduces daily average screen time use. These results are primarily influenced by responses from participants who were informed that their screen time use is higher than their self-perceived relative placement among their peers. Notably, this reduction is driven solely by behavioural motives, as the intervention is devoid of any financial incentives to curtail screen time use. Additionally, studying the relationship between screen time use and academic achievements shows suggestive evidence of a reduction in smartphone screen time being associated with an improvement in academic grades. Together, these results demonstrate the potential for carefully designed, information-based interventions to modify habitual behaviours and improve outcomes in terms of digital behaviour.

7.1 Appendix : Conceptual Framework

Here, I the optimal consumption choice under both the specific form of the utility function introduced in the conceptual framework.

7.1.1 Solving the Utility Maximization Problem

This section derives the optimal consumption choice under the specific utility function introduced in the conceptual framework. The individual's decision problem is to maximize the following piecewise utility function:

$$u(c,r) = \begin{cases} c^{\frac{1}{2}} - \theta\lambda(c^{\frac{1}{2}} - r^{\frac{1}{2}})^2, & \text{if } r < c\ , \\ c^{\frac{1}{2}} - \theta(r^{\frac{1}{2}} - c^{\frac{1}{2}})^2, & \text{if } r \geq c. \end{cases}$$

Here, $u(c,r)$ denotes the utility from consuming c units of screen time, given a perceived reference level r. The first term, $c^{\frac{1}{2}}$, captures consumption utility, which is strictly increasing and concave (i.e., exhibits diminishing marginal utility). The second term represents the gain-loss utility, which penalizes deviations from the reference point.

I impose $\theta \in (0, 1)$ and $\theta\lambda \in (0, 1)$, allowing $\lambda > 1$ as long as the product remains below unity. Permitting $\lambda > 1$ is standard in behavioural economics to capture loss aversion—the notion that losses loom larger than gains.

Case 1 : $r < c$

In this case, the utility function becomes:

$$u(c, r) = \sqrt{c} - \theta\lambda(\sqrt{c} - \sqrt{r})^2.$$

To find the optimal consumption level c^* for utility maximization, the first order condition (FOC) implies:

$$\frac{\delta u}{\delta c} = \frac{1}{2\sqrt{c}} - 2\theta\lambda(\sqrt{c} - \sqrt{r}) * \frac{1}{2\sqrt{c}} = 0$$

This simplifies to:

$$\frac{1}{2\sqrt{c}}(1 - 2\theta\lambda(\sqrt{c} - \sqrt{r})) = 0$$

Solving this yields the interior solution for c^*, as a function of $r, \theta \& \lambda$ which is given by:

$$c^* = \left(\sqrt{r} + \frac{1}{2\theta\lambda}\right)^2$$

From the first order condition for utility maximization:

$$\frac{1}{2\sqrt{c}} - \frac{\theta\lambda(\sqrt{c} - \sqrt{r})}{\sqrt{c}} = 0$$

we now consider the second derivative to verify concavity. The second-order condition is given by:

$$\frac{\delta^2 u}{\delta c^2} = -\frac{1}{4c^{3/2}} + \theta\lambda\sqrt{r}\left(\frac{-1}{2c^{3/2}}\right)$$

This expression is strictly negative for all $c > 0$ under the assumptions. Therefore, the utility function is strictly concave in c, and the critical point c^* identified by the first-order condition corresponds to a unique maximum.

Case 2: $r \geq c$

In this case, the utility function becomes:

$$u(c, r) = \sqrt{c} - \theta(\sqrt{r} - \sqrt{c})^2$$

To find the optimal consumption level c for utility maximization, the first order condition (FOC) implies:

$$\frac{1}{2\sqrt{c}} - 2\theta\left(\sqrt{r} - \sqrt{c}\right) \cdot \left(\frac{-1}{2\sqrt{c}}\right) = 0$$

Solving this yields the interior solution for c, given by:

$$c^* = \left(\sqrt{r} + \frac{1}{2\theta}\right)^2$$

However, this solution lies outside the admissible range, since $c^* > r$ by construction, above. Within the domain $c \leq r$, the utility function is strictly increasing in c as long as $\frac{du}{dc} > 0$, which holds for all $c < \left(\sqrt{r} + \frac{1}{2\theta}\right)^2$. Therefore, the local maximum within the feasible region occurs at the upper bound $c = r$.

Choice of consumption

We consider the consumer's utility-maximizing choice under the piecewise utility function:

$$u(c, r) = \begin{cases} c^{\frac{1}{2}} - \theta\lambda(c^{\frac{1}{2}} - r^{\frac{1}{2}})^2, c^* = (r^{\frac{1}{2}} + \frac{1}{2\theta\lambda})^2 & \text{if } r < c \ , \\ c^{\frac{1}{2}} - \theta(r^{\frac{1}{2}} - c^{\frac{1}{2}})^2, c^* = r & \text{if } r \geq c. \end{cases}$$

Substituting the optimal value of consumption c^* into the utility function yields:

$$u(c^*, r) = \begin{cases} r^{\frac{1}{2}} + \frac{1}{4\theta\lambda} & \text{if } r < c \ , \\ r^{\frac{1}{2}} & \text{if } r \geq c. \end{cases}$$

Therefore, the consumer will choose $c^* = (r^{\frac{1}{2}} + \frac{1}{2\theta\lambda})^2$ when :

$$r^{\frac{1}{2}} + \frac{1}{4\theta\lambda} > r^{\frac{1}{2}} \implies \frac{1}{4\theta\lambda} > 0$$

Since $\frac{1}{4\theta\lambda} > 0$ for all $\lambda > 0$, the consumer always achieves higher utility in the $c > r$ range. Therefore, the optimal consumption choice is:

$$c^* = \left(\sqrt{r} + \frac{1}{2\theta\lambda}\right)^2 \quad \text{for all } \lambda > 0$$

A simple comparative statics exercise illustrates that the optimal consumption level c^* increases with the reference point r.

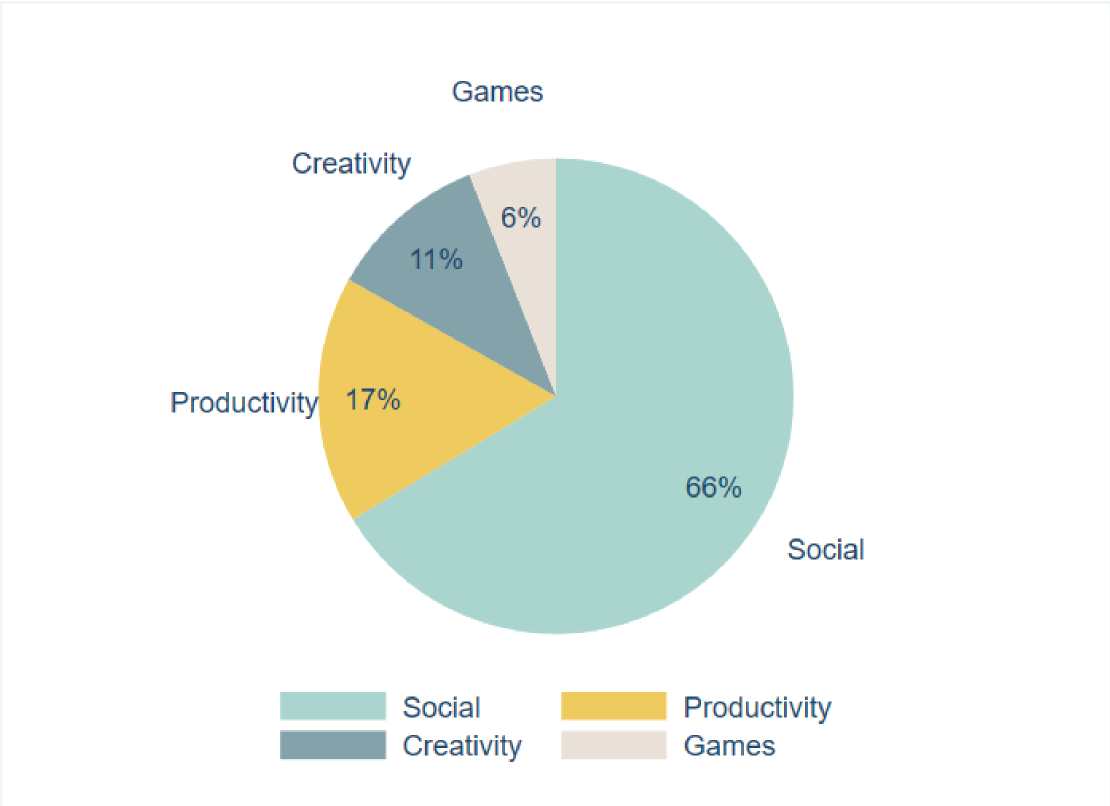
When $c^* = \left(r^{1/2} + \frac{1}{2\theta\lambda}\right)^2$, we have:

$$\frac{\delta c^*}{\delta r} = \left(1 + \frac{1}{2\theta\lambda\sqrt{r}}\right) > 0.$$

This implies, optimal consumption moves in the direction of the reference point, which is consistent with norm-following behaviour and reference-dependent adjustment.

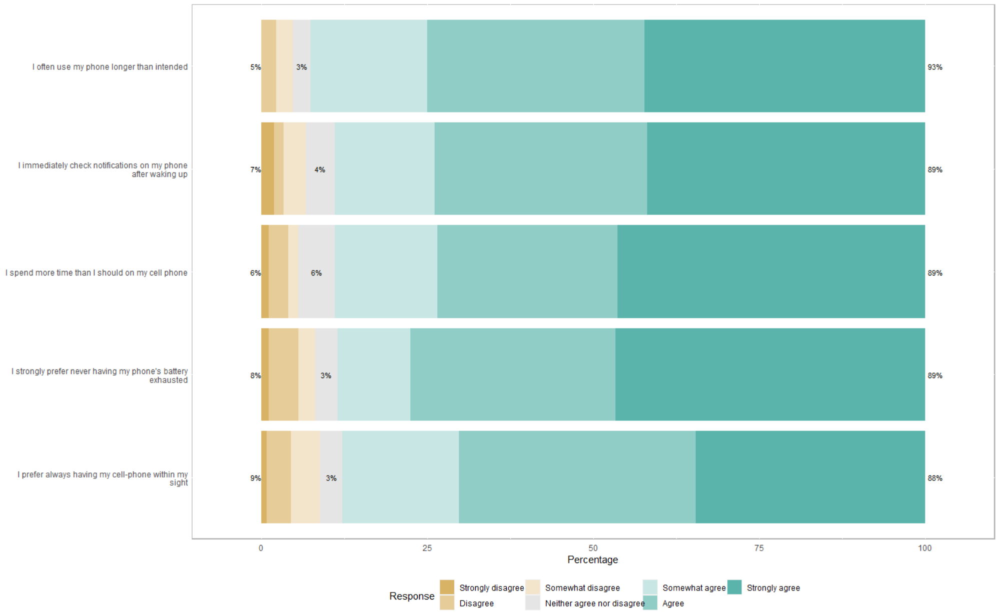
7.2 Appendix: Figures

Figure 4: Distribution of screen time use



The pie-chart shows the distribution of screen time across the built-in categories Social, Productivity, Creativity and Games for iOS users prior to the intervention.

Figure 5: Smartphone Dependence



The graph displays the answers to the questions that comprise the Smartphone Dependence Score.

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8 Appendix: Heterogeneous Treatment Effects

Table 10: Heterogeneous treatment effects by gender

Variables	Coefficient
Treatment	-10.13
	(13.00)
$T_i = 1$ & Gender = Male	-9.473
	(17.94)
Baseline Screen Time	0.829***
	(0.0514)
Gender	Yes
Commute	Yes
Software	Yes
Monitoring	Yes
Partner	Yes
Program	Yes
Year of Study	Yes
Enrollment	Yes
Smartphone Dependence Score	Yes
Constant	2.146
	(33.87)
Observations	199
r-squared	0.771

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The outcome variable is post-treatment average daily screen time in minutes. This table reports heterogeneous treatment effects by gender. All models include the full set of controls. Robust standard errors are reported in parentheses.

Table 11: Heterogeneous treatment effects by commute time

Variables	Coefficient
Treatment	-14.76
	(17.88)
$T_i = 1$ & Commute: 20–29 minutes	6.726
	(23.85)
$T_i = 1$ & Commute: 30 min − 1 hr	0.0452
	(25.85)
$T_i = 1$ & Commute: $<$ 10 minutes	-9.415
	(26.52)
Baseline Screen Time	0.828***
	(0.0522)
Commute Duration	Yes
Gender	Yes
Software	Yes
Monitoring	Yes
Partner	Yes
Program	Yes
Year of Study	Yes
Enrollment	Yes
Smartphone Dependence Score	Yes
Constant	5.417
	(29.14)
Observations	199
r-squared	0.771

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The outcome variable is post-treatment average daily screen time in minutes. This table reports heterogeneous treatment effects by commute time. All models include the full set of controls. Robust standard errors are reported in parentheses.

Table 12: Heterogeneous treatment effects by software (iOS vs. Android)

Variables	Coefficient
Treatment	3.265
	(18.86)
$T_i = 1$ & Software = iOS	-21.63
	(21.77)
Baseline Screen Time	0.828***
	(0.0506)
Software (iOS)	Yes
Gender	Yes
Commute	Yes
Monitoring	Yes
Partner	Yes
Program	Yes
Year of Study	Yes
Enrollment	Yes
Smartphone Dependence Score	Yes
Constant	-5.910
	(32.55)
Observations	199
r-squared	0.772

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Outcome is post-treatment average daily screen time (in minutes). This table presents heterogeneous treatment effects by mobile operating system. All models include full controls. Robust standard errors are reported in parentheses.

Table 13: Heterogeneous treatment effects by monitoring device

Variables	Coefficient
Treatment	-12.38
	(20.56)
$T_i = 1$ & Monitoring = Yes	-3.556
	(22.82)
Baseline Screen Time	0.827***
	(0.0521)
Monitoring	Yes
Gender	Yes
Commute	Yes
Software	Yes
Partner	Yes
Program	Yes
Year of Study	Yes
Enrollment	Yes
Smartphone Dependence Score	Yes
Constant	6.897
	(30.69)
Observations	199
r-squared	0.771

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Outcome is post-treatment average daily screen time (in minutes). This table presents heterogeneous treatment effects by whether participants used a monitoring app. All models include full controls. Robust standard errors are reported in parentheses.

Table 14: Heterogeneous treatment effects by relationship status

Variables	Coefficient
Treatment	-12.36
	(10.17)
$T_i = 1$ & Partner = Yes	-12.84
	(20.88)
Baseline Screen Time	0.828***
	(0.0510)
Partner	Yes
Gender	Yes
Commute	Yes
Software	Yes
Monitoring	Yes
Program	Yes
Year of Study	Yes
Enrollment	Yes
Smartphone Dependence Score	Yes
Constant	6.624
	(30.98)
Observations	199
r-squared	0.771

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Outcome is post-treatment average daily screen time (in minutes). Table reports heterogeneous treatment effects by relationship status. All models include full controls. Robust standard errors are reported in parentheses.

Table 15: Heterogeneous treatment effects by program.

Variables	Coefficient
Treatment	-14.44
	(12.69)
$T_i = 1$ & Program = BSc Retail Management	-34.58
	(39.45)
$T_i = 1$ & MBM Business Management	-4.217
	(24.85)
$T_i = 1$ & MSc AVFM	-7.646
	(26.87)
$T_i = 1$ & MSc Economics	-9.590
	(40.74)
$T_i = 1$ & MSc Finance	9.801
	(28.59)
Baseline Screen Time	0.828***
	(0.0540)
Program	Yes
Gender	Yes
Commute	Yes
Software	Yes
Monitoring	Yes
Partner	Yes
Year of Study	Yes
Enrollment	Yes
Smartphone Dependence Score	Yes
Constant	4.107
	(32.27)
Observations	199
r-squared	0.772

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Outcome is post-treatment average daily screen time. Table reports heterogeneous effects by academic program. Full controls included. Robust Standard errors are reported in parentheses.

Table 16: Heterogeneous treatment effects by year of study.

Variables	Coefficient
Treatment	-11.14
	(13.74)
$T_i = 1$ & Year = Second	-19.89
	(19.04)
$T_i = 1$ & Year = Third	13.92
	(25.14)
Baseline Screen Time	0.826***
	(0.0518)
Year of Study	Yes
Gender	Yes
Commute	Yes
Software	Yes
Monitoring	Yes
Partner	Yes
Program	Yes
Enrollment	Yes
Smartphone Dependence Score	Yes
Constant	3.283
	(31.85)
Observations	199
r-squared	0.773

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. This table presents heterogeneous treatment effects by year of study. The dependent variable is post-treatment average screen time. All models include full controls. Robust standard errors are reported in parentheses.