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Sleep and mobile phone use habits: Effects of reflection and information behavioral interventions

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Abstract

In this paper, we (i) map the mobile phone use and sleep habits of a representative sample of the Norwegian population; and (ii) investigate the effects of three different behavioral interventions (information, reflection-relaxation-sleeping-techniques, and reflection-mobile phone-use-habits) to change mobile phone use and sleeping routines. In relation to mobile phone use and sleep habits, we find differences between the age groups when it comes to the reported causes of poor sleep. The results also show that the proportion of respondents who think that the mobile phone is addictive is the largest among the youngest respondents. In addition, it is the youngest respondents who find it most difficult to put away the mobile phone before bedtime. In relation to the behavioral interventions, we find no significant effects on the treatment groups on the outcome variables relative to the control group. This shows the need to consider other types of behavioral interventions, regulation, or restrictions to change sleep and mobile phone use habits.

JEL Classification: D91; I12; I31

Keywords

Mobile phone — mobile dependence — sleeping habits — behavioral intervention — boost — nudge – survey experiment

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Introduction

Establishing and maintaining healthy sleep habits is frequently emphasized as crucial for general well-being and public health (Norwegian Institute of Public Health, 2022). However, research indicates an increasing prevalence of insomnia in countries such as Norway since the early 2000s (Bjorvatn, 2010; Bjorvatn et al., 2017; Norwegian Institute of Public Health, 2022). This poses a concern, as insomnia is linked to reduced work performance (Kessler et al., 2011), a markedly higher risk of academic underachievement, and challenges related to mental health and depression (Akyol et al., 2021; Taylor et al., 2011; Vally and El Hichami, 2019; Vedaa et al., 2019).

Human behavior traits and modern habits, such as the use of mobile phones, can be important explanatory variables for this challenging social trend. A meta-analysis of 24 countries found that problematic mobile phone use has been increasing in the past decade, especially among young people (Olson et al., 2022). For instance, young adults across the world spend on average two to three hours per day just on social media (GlobalWebIndex, 2021).

In this paper, we present the results of a study that aims to examine the effect of three behavioral interventions on reported motivation to change sleep and mobile phone use habits. Two of the interventions emphasize reflection on the positive outcomes linked to reduced screen time and relaxation sleeping techniques. These two interventions are usually classified in literature as a nudge. A nudge is a relatively simple "push" to a desirable change (individually and socially) in behavior while still preserving the individual's capacity to choose (Thaler and Sunstein, 2008). The third intervention was crafted as information based on research findings on the benefits associated with limiting screen time. This intervention is usually classified in literature as a boost.

Common to all these behavioral interventions is that they leave much freedom to subjects to change their behavior. Behavioral interventions that keep individual freedom are popular amongst politicians in liberal democratic countries as a policy tool, since they do not involve regulation and bans and are therefore easy and less costly to implement and usually face less resistance from voters (Ledderer et al., 2020). It is then important to assess when these behavioral tools might work and when they might not work.

Our study involves 1,072 respondents of a representative sample of the Norwegian population. We pay particular attention to age, since as mentioned, mobile phone use is highest and more problematic among young people (Gradisar et al., 2011; He et al., 2020; Hysing et al., 2015; Kalk et al., 2021; Sohn et al., 2021).

In comparison to a control group that did not receive any intervention, our findings indicate no statistically significant effects on the treatment groups on outcome variables such as motivation to alter existing sleeping habits. Our results point out that the type of behavioral interventions used in this study can have limited effect when ingrained habits or addictive behaviors (as is the case with the mobile phone) are involved.

Theoretical Mechanism and Choice of Behavioral Interventions

The problem associated with mobile phone use and sleeping habits can be seen through two behavioral mechanisms. First, when using a mobile phone people can face a time-inconsistency problem, in the sense that preferences might change between the "now" moment and the "future" moment; see Allcott et al. (2022). For instance, people might be aware that it is not good to use the mobile phone before sleep because it affects sleeping routines. Therefore, they may say that they will not use the mobile phone when night comes. However, when the time to go to bed arrives, they check a social media app, and only two hours later they finally go to bed. This example shows why time-inconsistency is often related to self-control issues.

Second, mobile phone use (for example again social media apps) can lead to (bad) habits of spending too much time online; for a review see James et al. (2023). In the worst-case scenario, mobile phone use can become an addiction and lead to compulsive behavior of being always with mobile phone in hand "to not miss out on something" what is happening online.

These two channels have been explored in the literature on mobile phone use. Starting with time inconsistency; Allcott et al. (2022) using randomized experiment present evidence that indeed people have self-control problems with social media. However, they also show that setting limits on future screen time can reduce mobile phone use. Wang et al. (2024), in turn, show a positive correlation between mobile phone use and time management among Chinese college students. In a randomized experiment, Hoong (2021) presents evidence that subjects use social media more than they predict and desire, which indicates again problems with self control. Hoong (2021) however shows that commitment devices, like limiting social media usage, can help to reduce the use of mobile phone.

In terms of habits and addiction, Duke and Montag (2017) present evidence that mobile phone habits and addiction are closely connected with the use of mobile phone in leisure time. This in turn influences productivity in the workplace. Allcott et al. (2022) show that social media use leads to habit formation, and that people are usually unaware of this. Park et al. (2021) demonstrate that the predictors of addictive mobile phone use are being active on social media, shopping, games, and entertainment apps, average weekend smartphone usage time, and sleep duration. In turn the predictors of habitual mobile phone use are use of web and lifestyle apps, weekly usage frequency, and being female. Jo and Baek (2023) show that the flow of use, perceived enjoyment and habit of use can be the first step that leads later to addiction in mobile phone use.

The results of Duke and Montag (2017), Allcott et al. (2022) and Jo and Baek (2023) point out to one important issue: time-inconsistency problems can lead to habit formation and addiction in the context of mobile phone use. Accordingly, those that believe that there is no problem in checking their mobile phone occasionally (for instance for social media updates), because they are strong enough to not create a habit, are those that most likely will use the mobile phone more heavily and more regularly and that in the end will become addicted to it. In this sense, it seems to be central to first make people aware that everyone can fall prey to time-inconsistency problems, and second to prevent people from using the mobile phone so little as possible. The behavioral intervention in this study tries to work through these two mechanisms. Accordingly, the information boosts aim at raising awareness on the problems associated with mobile phone use and sleep problems. In turn the reflexive nudges aim at keeping to a minimum the use of mobile phone.

In turn, the literature on mobile phone use and sleeping habits can be divided into two strands[1]: one that uses experiments and can therefore establish causal relations; and another that uses cross-sectional studies and therefore can only give correlations. As we will see, however, many of the existing experimental studies suffer from small samples.

Regarding experimental studies. Bartel et al. (2019) study adolescents' mobile phone using habits and sleep patterns in a sample of 63 subjects. Their experiment consists in restricting mobile phone use before sleeping with the help of an online sleep diary that monitors bedtime, lights out time, sleep latency and total sleep. The online sleeping diary proved to have a positive impact on the adolescents that adopted it. However, only a small share of the subjects adopted the online sleeping diary (26%). Due to the low adoption rate of the sleeping diary, the authors suggest using non-technological interventions, since technological interventions might be perceived as more invasive by subjects, leading to lower adoption of these solutions. He et al. (2020) perform a field experiment with 38 respondents, where subjects in the treatment group were instructed to avoid using the mobile phone before bedtime. This intervention had positive effects in reducing sleep latency, increasing sleep duration, improving sleep quality, reducing pre-sleep arousal. As for the previous study, however the sample was too small, which again restricts severely the power of the results.

In addition to the experimental studies there are also a couple of cross-section studies. Hysing et al. (2015) use a large cross-sectional adolescent (self-reported) survey study in Hordaland County in Norway. They find, as expected, that adolescents use mobile phone heavily both during the day and before bedtime. They also show a negative correlation between the use of mobile phone and sleep quality. In relation to the experimental studies above, this one has the advantage of

[1] We do not review the literature on sleeping habits since this is extremely large. For a review of the sleep literature see for instance Gradisar et al. (2011), Kessler et al. (2011), Taylor et al. (2011) and Ramar et al. (2021).

having a large sample, but the disadvantage is that the results are just correlations, since it is a cross-sectional study. Sohn et al. (2021), like Hysing et al. (2015), also use a large cross-sectional sample, with young adults from the UK. They find that a large share of the sample (39%) reported smartphone addiction. In addition, they find that smartphone addiction is associated with poor sleep. Again, as for Hysing et al. (2015), this study can only show correlations but not causality.

Choice of Behavioral Interventions

The choice of behavioral interventions in this study was driven by two factors. First, the theoretical mechanism for over-use of mobile phone. As discussed above, these mechanisms are time-inconsistency (self-control problems) and/or habit and addiction. The second reason is motivated by policy viability.

Regarding the theoretical reasons; in the literature it has been shown that self-control problems can be tackled with commitment devices, which can be hard or soft (Bryan et al., 2010). Bryan et al. (2010) define hard commitment devices as those "that call for real economic penalties for failure, or rewards for success". In turn, they define soft commitment devices as devices that have "primarily psychological consequences". Bryan et al. (2010) give the following examples for soft and hard commitment devices: "An example of a hard commitment would be a commitment savings account on which interest is forfeited if a monthly deposit is not made [...] A soft commitment would be a separate savings account labeled 'send kids to college'; if someone withdraws money from that account to pay for a holiday party, he or she incurs costs that are primarily psychological, such as disappointment...".

In this sense, hard commitment devices are usually more invasive and costly for subjects. The same occurs with restrictions and bans.[2] This relates with the second reason for the choices of behavioral interventions in this study: policy. In what concerns mobile phone use, politicians and policy makers have been showing a preference for a more hands-off approach, i.e. leaving to individuals their choice in terms of mobile phone use. This can be seen for example in the public debate about allowing or not allowing mobile phone use by kids and adolescents at school, where the discussion has been between bans and a more hands-off approach. Aksoya et al. (2023) report that in recent years there has been a decline in the number of schools that ban mobile phone use, in part because parents demand that they can reach their kids during schooling hours. As a result, schools have been trying interventions that give freedom to students to reduce mobile phone use.

For young adults and adults, the emphasis has been even more about leaving to individuals to decide how they use the mobile phone, although, advising them to use less mobile phone. The same is in fact the case with sleeping habits. Accordingly, when it respects mobile phone use and/or sleeping habits, many people believe that this is the responsibility of individuals and that restrictions and prohibitions are very invasive.

To the best of our knowledge, Collis and Eggers (2019) is an exception in using interventions that restrict social media usage by students. In their field experiment, social media usage is limited to a maximum of 10 minutes per day. The experiment however had a non-intended effect since students substituted social media for instant message services therefore not reducing mobile phone use. This substitution effect shows the limits of using restrictions (or bans) in what respects mobile phone use. Accordingly, even if we ban completely the use of the mobile phone, people can use computers or other electronic devices, like gaming devices for instance. In this sense, behavioral changes must be accompanied by a change in mindset regarding the use of any type of electronic device, which can only be achieved if people internalize the consequences of it. In this sense, behavioral interventions that do not imply bans or restrictions can be thought of as an intervention that can be effective in this respect since they appeal to people's conscience in the use of the mobile phone and/or other electronic devices.

One of our aims in this study is then to see if behavioral interventions that do not imply restrictions or bans can be successful in reducing mobile phone use and in this way have a positive impact on sleeping habits. The second motivation is that there are very few studies on the effects of behavioral interventions on mobile phone use and sleeping habits. As mentioned above, the studies that look at this suffer from small samples, or they are just correlation studies. Hoong (2021) looks at nudges but only look at mobile phone use. Hoong (2021) finds that nudges can influence mobile phone use. So, our aim is also to see if that extends to sleeping habits.

Lastly, we want to go back to theory, since we have still not discussed one aspect of it: habits and/or addiction. All of what we have said above applies more to habits, but not so much to addiction. Accordingly, habits are difficult to change but even so are easier to change than addictions. Addictions are ingrained behavior that often is even compulsive, something that we cannot avoid regardless of how much willpower we have. In the case of addiction, we expect that boosts and nudges, have less power to change behaviors; see the discussion in Allcott et al. (2022); Sohn et al. (2021).

Hypotheses

From the above discussion on the theoretical justifications for the behavioral interventions used in this study, we have then decided to explore three types of behavioral interventions: information; reflection relaxation and reflection mobile phone use.[3] The information boost aims to give subjects information about the negative aspects of using the mobile phone before

[2] Restrictions or bans can either be regulated by regulatory authorities or not. For instance, an app can allow users to restrict how much time they can use this app. Note that restrictions and bans are not considered a nudge, since for being classified a nudge, the individual still has the last word.

[3] These types of behavioral interventions have been shown to be important tools in several social domains; see for example, Bjorvatn et al. (2021) for the impact on goal setting nudges on labor market outcomes.

going to sleep. Note that the information boost can also potentially affect subjects that are already aware of the problems related to mobile phone use and sleeping habits. For these subjects, the information boost works more as a reminder.

The reflection on mobile phone use aims to lead subjects to think about their use of mobile phone and lead them to conclude that reducing the use can lead to better sleeping habits. The reflection relaxation aims to incentivize subjects to use relaxation techniques before sleep instead of using the mobile phone. These types of behavioral tools have been hypothesized to have potential positive effects in healthy lifestyle interventions, see Thaler and Sunstein (2008), Ledderer et al. (2020) [4].

In terms of outcomes, we measure the following variables: (1) willingness to use less mobile phone before bedtime; (2) agree that sleep is important to function optimally in daily life; (3) willingness to use more resources (time, money, effort, and learning) to improve sleep patterns; (4) willingness to prioritize having enough sleep in a daily basis; (5) recommend relaxation techniques to others who struggle with sleep; (6) motivation to change existing habits to improve sleep. We then have as a main hypothesis that behavioral interventions can have a positive impact on (at least some) of these outcome variables.

We also control for demographics (gender, age, and education) and habits (difficult to put the mobile phone away, satisfied with sleep, takes active steps to achieve better sleep, pace of daily life, talks to networks about sleep, seeks confirmation, is structured, and trusts research) and habits and reasons for bad sleep (self-reported reasons for bad sleep and desire to use mobile phone less before bedtime). In the choice of variables, we pay particular attention to the variables that can indicate self-control problems (takes active steps to achieve better sleep and desire to use mobile phone less before bedtime) and addiction (difficult to put the mobile phone away).

Our hypotheses are the following:

H1: Behavioral interventions can lead subjects to reduce self-reported mobile phone use before sleep, which in turn may promote better sleeping habits.

H2: Behavioral interventions are more likely to have a positive impact on mobile phone use and sleeping routines if they successfully address self-control problems.

H3: Behavioral interventions have greater potential to be effective when subjects are not struggling with addiction-related problems associated with mobile phone use.

Despite their potential, the literature on boost and nudges has shown that their effects can be mixed (Kozman and Sander, 2019; Maier et al., 2022; Mertens et al., 2022; Osman and Baddeley, 2019). An important reason for this is that behavior is context-specific and for instance a nudge that changes people's eating habits need not, for instance, to affect people's exercise or sleep habits. It is then central to assess which behavioral interventions work in specific situations as is the case with mobile phone and sleeping habits.

Ethical Concerns

One of the reasons that governments and policy makers prefer behavioral interventions that leave to individuals the final decision is that they are less invasive and therefore they respect more individual freedoms. This is especially the case with restrictions and bans. The other issue is privacy, since having access to a person mobile phone log, social media use, gaming behavior might not be acceptable at least in a continuous way. For these reasons, behavioral interventions like boosts and nudges suffer from less severe ethical issues than restrictions and bans.

Methods

The main method used in this paper is an online survey experiment. In a typical experiment, a random group receives a measure (treatment group), whereas another random group does not (control group). Afterwards, it is analyzed whether the measure given to the treatment group has any effect on the behavior of group members relative to the control group. As assignment to the intervention is random, we can identify the causal effect of the treatment(s) on the outcome variable.

Design

The respondents started the survey with an introductory text that presented the topic and length of the survey.[5] Respondents were informed about anonymity and the possibility to withdraw. Figure 1 shows the steps in the study that the respondents went through.

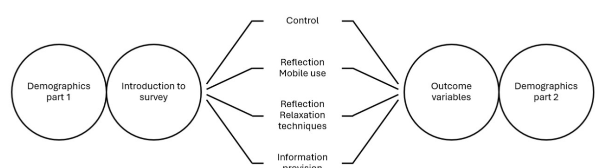

Figure 1. Experimental design

In the Norstat panel, some socio-demographic questions come at the beginning of the survey to give respondents a smoother entry to the survey, whereas others are asked in the end. After the introductory text, respondents answered questions about their existing sleep habits.[6] Respondents then

[4]In another context, Balafoutas et al. (2018) use reflection nudges to increase competitiveness in women.

[5]All the data was collected by Norstat and the randomization is a simple randomization. Information about the survey company in Norway can be found here: https://norstat.co/. See Appendix for more details about Norstat.

[6]Randomization ensures that any potential priming following the questions eliciting existing habits is spread equally across groups. This means that differences between groups can still be attributed to the treatment, which preserves causal inference.

answered questions directly related to their mobile phone use habits.

The 1,072 respondents were then randomized into four mutually exclusive groups with 268 respondents in each (see Table A1 in the Appendix). In the Reflection Mobile Use group, respondents were asked to write down three positive effects they believed they could obtain from reducing screen time (for example, putting away the mobile phone earlier, not watching TV and/or iPad) in the evening. In the Reflection Relaxation group, respondents were asked to write down three positive effects they think they could obtain from relaxation techniques (for example, guided meditation, soundtracks to aid falling asleep, and breathing exercises). See Table A2 in appendix for some typical answers given by the subjects.

In the Information group, respondents received research information stating that it is possible to improve one's own sleep by taking conscious steps such as putting away their mobile phone before bedtime and that good sleep reduces the risk of several diseases, including heart problems, dementia, depression, anxiety, and diabetes (He et al., 2020; Ramar et al., 2021). In the Control group, respondents did not receive any information and were not asked to reflect. Furthermore, all respondents were asked to answer questions about their willingness to use resources to achieve better sleep, the number of hours they aimed to sleep the night of the survey, and how likely it was that they would use their mobile phone less in the weeks ahead. These are the outcome variables in this study. To avoid so-called "anchor effects", or sequence effects, these questions were asked in random order.

Results and Discussion

Sample description

The sample consisted of 1,072 respondents that are representative of the Norwegian population (see Figure 2 for age distribution). There is a good balance in terms of observable characteristics such as age, sex, municipality, county, income, and education level across the three treatment groups and reference group. There were somewhat more women in the Reflection Relaxation group (Chi2(3) = 7.2950, p = 0.063).[7] Likewise, there were a few more highly educated respondents in the Information Provision group (Chi2(3) = 6.9358, p = 0.074). In the regression analysis, we controlled for relevant observable characteristics and existing sleep and mobile phone habits.

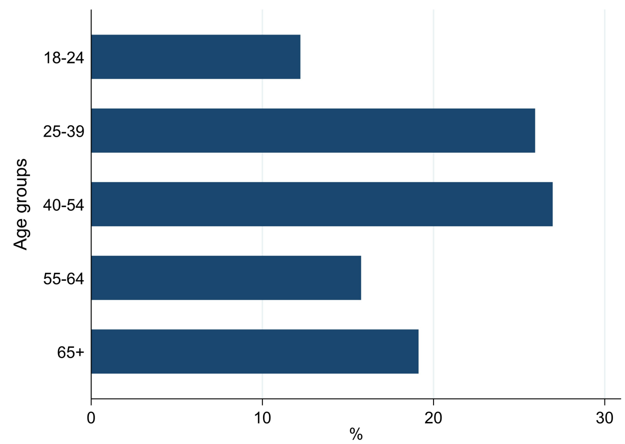

Figure 2. Age distribution in the sample (%)

Respondents' sleeping habits

In the sample, 33 percent of respondents reported that their life was either high- or very high-paced, whereas 15 percent reported that their pace was low or very low. Figure 3 shows the distribution of pace broken down by respondent's age. The proportion who had a fast-paced life was highest among those aged 25–39 years and 18–24 years and decreased the older the respondent was. The differences between age categories and pace are statistically significant.

Most (35 percent) of the respondents reported that they slept seven hours each night, 19 percent slept six hours, whereas 13 percent slept eight hours. We find statistically significant differences in the number of hours different age groups typically sleep on a regular night (Chi2(4) = 34.084, Prob = 0.0001). When respondents were asked to guess how many hours others who are like them slept, 48 percent expected others to sleep seven hours. Twenty-four percent expected others to sleep eight hours. There is thus a gap between one's own sleep habits and what respondents thought about others that are like themselves.

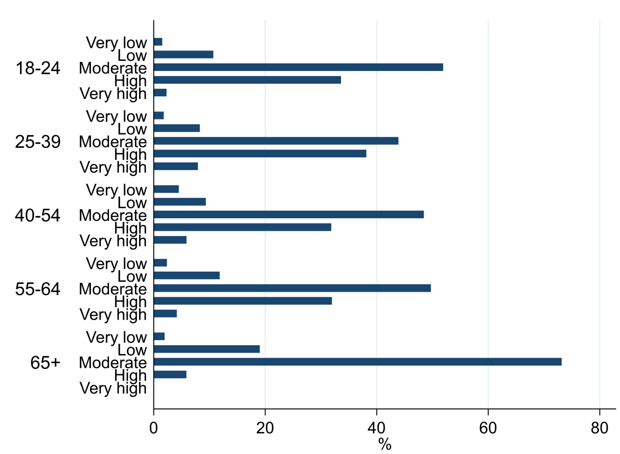

Figure 3. Pace of life divided by age (%)

However, we want to acknowledge that the survey context (asking about sleep/mobile phone use first) could have raised awareness and shifted how all respondents respond – making their self-reported behaviour and attitudes slightly different than if they had been treated "cold."

[7]The Chi2 (Chi-squared) test is a non-parametric statistical test used to determine whether there is a significant association between two categorical variables. These tests can say something about statistically significant differences between treatments, but they do not say anything about the strength of these relationships, nor do they include control variables.

Most respondents said that they either had enough sleep on two nights (17 percent), five nights (18 percent), or seven nights (18 percent) a week (Figure 4). Among the youngest respondents (18–24 years), it was most common to have five nights with enough sleep. For those in the age category 25–39, it was most common to have two nights with enough sleep. Figure 4 shows the distribution. The differences in the quality of sleep are significantly different between age groups (Chi2(4) = 122.687, Prob = 0.0001).

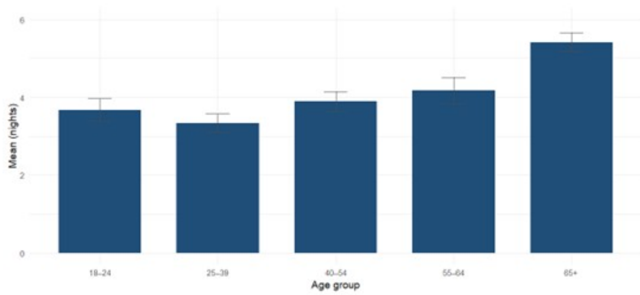

Figure 4. Number of nights the respondents had enough sleep in a typical week (95% Confidence Interval)

The respondents were neither very dissatisfied nor very satisfied with their sleep quality (36 percent vs. 38 percent). Figure 5 shows how satisfied respondents were with their sleep quality across age groups. The oldest respondents (65+ years) were the most satisfied, whereas the younger respondents were less satisfied with their sleep quality.

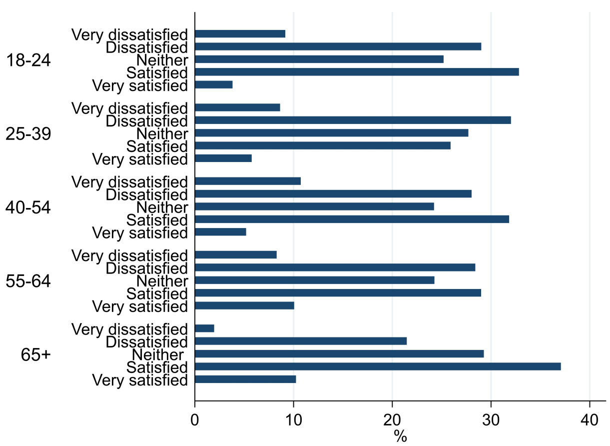

Figure 5. Satisfied with sleep quality (%)

In general, respondents reported that they suffered from poor sleep between none and three nights a week (approximately 69 percent). The group most often troubled by poor sleep was that of respondents in the 25–39 age group. See Figure 6. The youngest respondents suffered from poor sleep 2.5 nights per week. The differences between age groups are statistically significant (Chi2(28) = 45.2151 Pr = 0.021).

Figure 7 shows that there were differences in what was reported as reasons between the age groups. Circadian rhythm, screen time and stress were the dominant causes of poor sleep

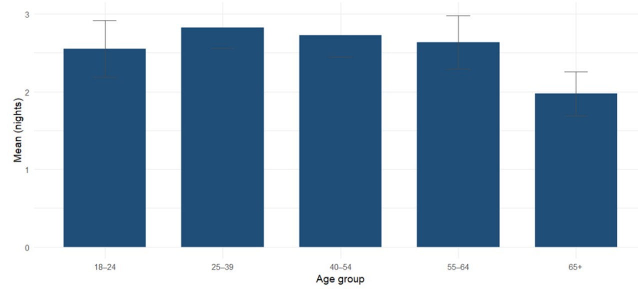

Figure 6. Number of nights per week troubled by poor sleep, average (95% Confidence Interval)

among those in the 18–24 age group. Among this age group, 70 percent reported that stress was the cause. In comparison, 63 percent reported the same among those aged 25–39 and 40 percent among those aged 40–54. The age group 25-39 is the age group most affected by children, as is in this age that many become parents.

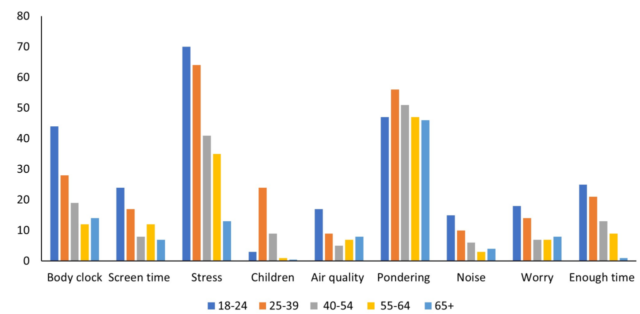

Figure 7. Reasons for poor sleep (%, several answers are possible)

Figure 8 shows the the most important reasons why sleep was important to the respondents by age group. Among the 18–24 and 25–39 age groups, mental health was the dominant reason. For example, 31 percent of respondents aged 18–24 believed that mental health was the most important reason why sleep was important, whereas 33 percent believed the same among those aged 25–39. For respondents aged 55–64, the most important reason (29 percent) was the ability to cope with work and other things. For respondents aged 65+, the most important reason (42 percent) was that it was good for personal well-being.

Actual mobile phone use habits

Approximately 57 percent of respondents thought it was difficult to put their phone away in the hour before going to bed. The youngest respondents found it most difficult to put their mobile phone away in the hour before bedtime.[8] For example, among respondents in the 18–24 age group, 79 percent believed that it was difficult to a certain extent. Among those aged 25–39, 70 percent thought the same.

[8]One respondent in the age group 65+ added 10099 minutes before bedtime. We removed this respondent before calculating the average and median overall and for the different age groups.

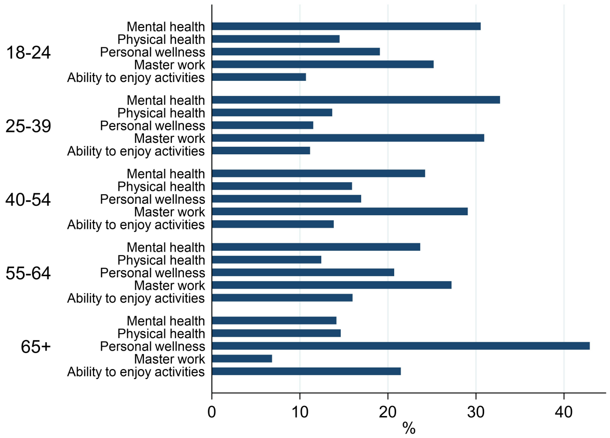

Figure 8. Most important reasons why sleep was important (%, one answer possible)

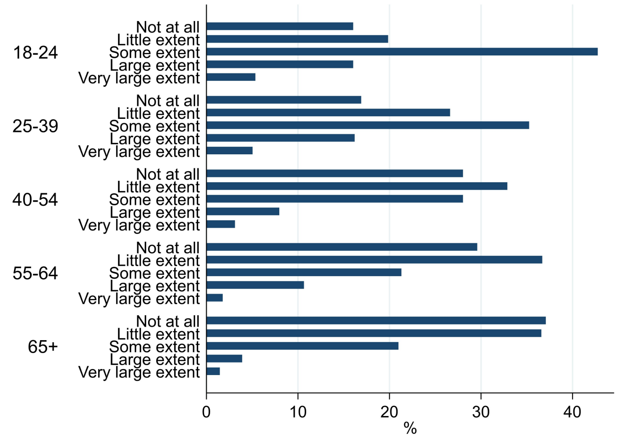

Figure 10. Desire to use mobile phone less before bedtime (%)

How difficult it was for respondents to put the mobile phone away before bedtime reflects how early they actually put the mobile phone away. Respondents reported that, on average, they put the mobile phone away 23 minutes before bedtime. The median was 10 minutes. Figure 9 shows that among those aged 18–24 years, the average time was 12 minutes. In comparison, respondents in the 55–64 age group put the mobile phone away approximately 26 minutes earlier on average. Those in the age group 65 and over put the mobile phone away almost 40 minutes before bedtime.

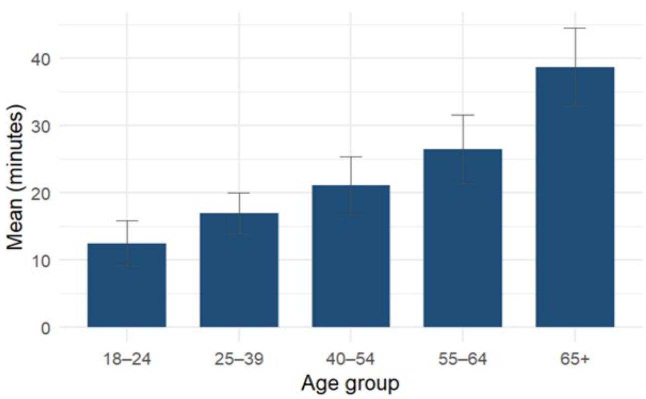

Figure 9. Age distribution of putting the mobile phone away, minutes before bedtime (95% Confidence Interval)

About 43 percent wanted to use their mobile phone less before bedtime. Figure 10 shows that approximately 64 percent in the 18–24 age group wanted to use their mobile phone less before bedtime. Fifty-six percent wanted the same in the 25–39 age group. Note that respondents who answered earlier that they found it difficult to put away their mobile phone had a greater desire to use their mobile phone less before bedtime compared to those who answered that it was not difficult.

In Figure 11, we observe that the youngest respondents were more inclined to use the mobile phone as an alarm, to be available, and to check news, emails, and social media. A significant difference between the youngest and oldest respondents was the view that the mobile phone is addictive. Thirty-one percent of those in the 18–24 age group thought the mobile phone was addictive compared with approximately 18 percent of those in the 25–30 age group and approximately six percent among those in the 40–54 age group.

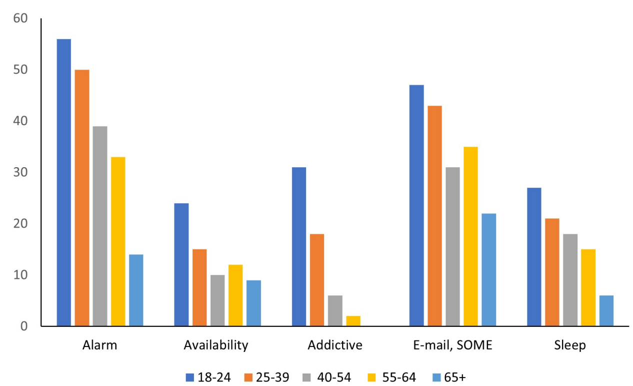

Figure 11. : Reasons why it was difficult to put the mobile phone away (%, several answers are possible)

Effects of behavioral interventions

To investigate the effect of behavioral interventions on relevant outcome variables, we estimate the following model:

$$y_i = \alpha + \beta_1 \text{Information}_i + \beta_2 \text{MobileUse}_i + \beta_3 \text{Relaxation}_i + \theta X_i + \varepsilon_i \tag{1}$$

where y_i is the outcome variable. We consider several alternative outcome variables. The label used for each outcome variable is given in parentheses, followed by the corresponding response scale:

- Use mobile phone less before bedtime in the coming week (*Use less*): Very likely, likely, neither likely nor unlikely, unlikely, very unlikely.

- Agreement that sleep is important to function optimally in daily life (*Optimal*): Strongly agree, agree, neither agree nor disagree, disagree, strongly disagree.
- Willingness to use resources (e.g., time, money, effort, and learning) to improve sleep (*Resources*): Very willing, willing, somewhat willing, unwilling, not willing at all.
- Priority given to having enough sleep in the coming time (*Priority*): Very high priority, high priority, medium priority, low priority, not a priority.
- Likelihood of recommending relaxation techniques to others who struggle with sleep (*Recommend*): Very likely, likely, neither likely nor unlikely, unlikely, very unlikely.
- Motivation to change existing habits to improve sleep (*Motivation*): Very motivated, motivated, neither motivated nor demotivated, demotivated, very demotivated.

The variables Relaxation_i, MobileUse_i, and Information_i measure the effects of the behavioral interventions in relation to Control_i which represents the group that did not receive a behavioral intervention. Vector $\mathbf{X}_i$ controls for respondents' gender, age, current sleeping habits, and current mobile phone use habits. Robust standard errors are used throughout the analysis.

Table 1 shows the effect of the behavioral interventions on the outcome variables just referred without controlling for the respondent's existing habits and characteristics, with ordinal logit estimates.[9] The control group serves as the baseline and the variables "Information", "Mobile use", and "Relaxation" are binary indicators (e.g., 1 = assigned to treatment, 0 = not assigned).

As can be seen from Table 1, behavioral treatments have mostly no statistically significant effects on the outcome variables. This indicates that the behavioral interventions in this study show little potential to change sleep and mobile phone use habits. The only exception to this is the "Resources" variable. Surprisingly however, the sign of this variable goes in the opposite direction of what we hypothesized. In other words, subjects in treatment group are less likely to use resources to reduce mobile phone use and have better sleeping habits than the control group. One possibility for this negative effect on "resources" is a "backfire effect". Accordingly, subjects may have become less willing to invest time/money/effort/learning in sleep improvement after receiving the behavioral interventions.[10]

This is an important and potentially policy-relevant finding.[11] In fact, the "resources" variable is the only one that explicitly involves personal cost, and other factors besides the treatment itself can be at stake here. Accordingly, when habits are very ingrained and there are possibly addiction components, people might resist investing in habit reduction because with addiction this implies higher mental/psychological costs to them. Next, we look at each of the outcome variables adding also controls to the regressions. Note that the estimated treatment effects represent effects conditional on the survey context established by the pre-treatment items.

Use mobile phone less before bedtime

Figure 12 shows how likely respondents thought it was that they would try to use their mobile phone less before bedtime in the coming weeks. The first observation is that there are no major differences across the three treatment groups and the reference group (Chi2(12), p = 0.744). This is also confirmed in column 1 of Table 1).[12]

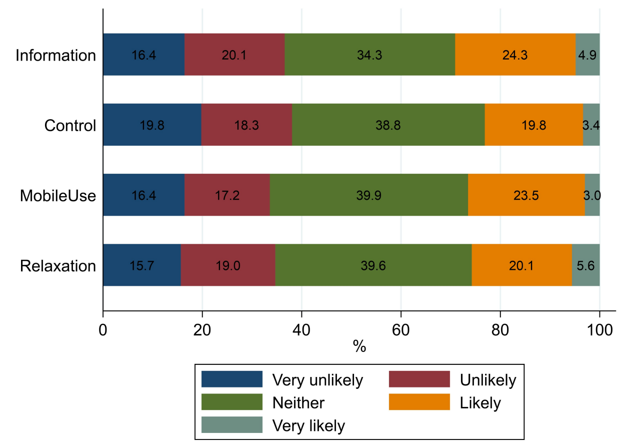

Figure 12. Respondents likely to try to use their mobile phone less before bedtime, across groups

Table 2 shows the effects of behavioral interventions on the likelihood of using mobile phone less with ordinal logit regression adding controls. We control for demographics (gender, age, and education) and habits (difficult to put the mobile phone away, satisfied with sleep, takes active steps to achieve better sleep, pace of daily life, talks to networks about sleep, seeks confirmation, is structured, and trusts research). We also control for habits and reasons for bad sleep (self-reported reasons for bad sleep and desire to use mobile phone

[9] We tested treatment effects across six outcome variables using ordered logistic regression. Following the suggestion of a referee, we also adjusted for multiple hypothesis testing and accounted for family-wise-error rate, by applying Holm-Bonferroni correction across the 18 comparisons (3 treatment groups × 6 outcomes). In appendix we show results with OLS regressions. See Tables A3, A4, A5, A6.

[10] Other possibility is that respondents thought they could improve their sleeping habits without investing additional time, effort, or learning. The result may also indicate that asking respondents to reflect on a topic that they were later asked about again increases what is referred to in social psychology as reactance – that one becomes less willing to do something or think something if this is expected by others, for example, a researcher (see Brehm and Brehm (2013).

[11] We are grateful to one anonymous referee for point out this.

[12] As pointed by one reviewer many of our R^2 are low. This is not unusual in survey-based social science research, particularly when studying attitudes and self-reported behaviors. These outcomes are shaped by a wide range of individual, contextual, and unobserved factors. See the discussion in Ozili (2023).

Table 1. Ordinal logit regressions without controls

	Use less	Optimal	Resources	Priority	Recommend	Motivation
Information	0.197	−0.173	−0.390*	−0.017	−0.213	0.138
	(0.157)	(0.172)	(0.157)	(0.163)	(0.154)	(0.167)
Mobile Use	0.184	0.267	−0.248	−0.089	−0.210	0.011
	(0.155)	(0.177)	(0.157)	(0.164)	(0.154)	(0.167)
Relaxation	0.180	0.046	−0.349*	−0.009	−0.024	−0.177
	(0.156)	(0.174)	(0.157)	(0.162)	(0.154)	(0.168)
Pseudo R^2	0.001	0.004	0.002	0.000	0.001	0.002
Observations	1,072	1,072	1,072	1,072	1,072	1,072

Notes: The table reports coefficient estimates from ordinal logit regressions without controls. Robust standard errors are reported in parentheses. Use less: desire to use the mobile phone less before bedtime in the coming week. Optimal: agreement that sleep is important to function optimally in daily life. Resources: willingness to use resources to improve sleep. Priority: priority given to obtaining enough sleep. Recommend: willingness to recommend relaxation techniques to others. Motivation: motivation to change existing habits.
$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

less before bedtime). The habits control variable "difficult to put the mobile away" is an indicator of addictive behavior in relation to mobile phone (H3). In turn the habits control variable "takes active steps to achieve better sleep" and the habits and reasons for bad sleep variable "desire to use mobile phone less before bedtime" is an indicator that subjects try to solve self-control problems in the use of mobile phone (H2).

We can see that adding controls does not significantly change the results. Meaning that again we not only do not find support for H1, but also not for H2 and H3. We nevertheless observe some interesting correlations. For example, respondents who believed that it was very difficult to put away the mobile phone were less inclined to reduce the use of the mobile phone, which can be interpreted as a symptom of addiction. We have also explored the interaction of 'treatment x hard to put the phone away', and we find two things: 1) being in the Relaxation treatment relative to the Control group significantly increases the likelihood of trying to improve sleep habits among individuals who do not struggle to put their phone away before bedtime (p<0.05), and 2) for those in the Relaxation treatment who struggle to put their phone away, the positive effect of relaxation techniques seems to be reduced (offset) (p<0.05).

Having poor sleep up to three times a week compared with never having problems sleeping was associated with a higher propensity of respondents to use their mobile phone less before bedtime. Likewise, respondents who had a faster pace of life were more inclined to use their mobile phone less before bedtime. Being more organized was associated with greater motivation to use their mobile phone less before bedtime.

Sleep is important to function optimally in daily life

Figure 13 shows the extent to which respondents agree with the statement that sleep is important to function optimally in daily life. The first observation is that there are some differences, but these are not large across the treatment groups and the reference group (Chi2(12) = 18.8859, p = 0.091). The absence of an effect at the 5% level is confirmed in Column 2 of Table 1.

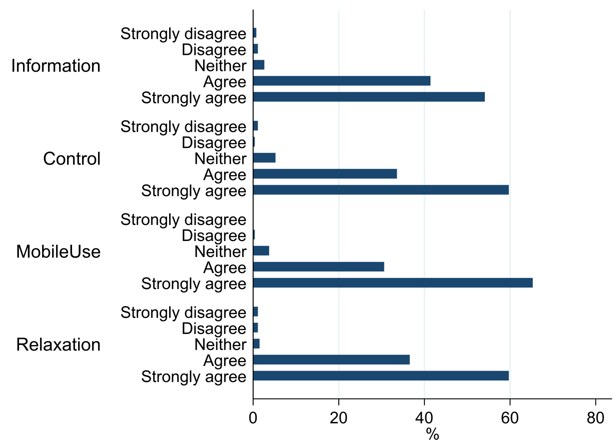

Figure 13. Agreed that sleep is important for optimal functioning across groups

The same can be seen from Table 3 that shows the absence of effects of behavioral interventions on agreement with the statement that sleep is important to function optimally ordinal logit regression, adding controls. We see that most results are not statistically significant. After controlling for habits and reasons for bad sleep the coefficients are again insignificant. Then once again we do not find support for H1, H2 and H3.

We further observe that respondents with a very high pace of life agreed more with the claim that sleep is important for functioning in daily life. Respondents who always took active steps to improve their sleep also agreed more with the statement that sleep is important compared with respondents who never took active steps. Compared with men, women agreed more with the same statement, whereas individuals in the 18–24 age group agreed significantly less when compared with older respondents.

Table 2. Effect on the likelihood of using mobile phone less (ordinal logit regressions) with controls

	(1) Likely	(2) Likely	(3) Likely	(4) Likely
Information	0.197	0.221	0.242	0.222
	(0.157)	(0.159)	(0.162)	(0.166)
Mobile Use	0.184	0.198	0.211	0.150
	(0.155)	(0.157)	(0.162)	(0.165)
Relaxation	0.180	0.207	0.254	0.213
	(0.156)	(0.158)	(0.163)	(0.171)
Pseudo R^2	0.001	0.002	0.066	0.150
Observations	1,071	1,059	1,059	1,059
Control demo	No	Yes	Yes	Yes
Control habits	No	No	Yes	Yes
Control habits and reasons	No	No	No	Yes

Notes: The table reports coefficient estimates from ordinal logit regressions. Robust standard errors are reported in parentheses. Control demo includes gender, age, and education. Control habits includes difficulty putting the mobile phone away, satisfaction with sleep, taking active steps to improve sleep, pace of daily life, talking to networks about sleep, seeking confirmation, being structured, and trust in research. Control habits and reasons additionally include self-reported reasons for poor sleep and the desire to use the mobile phone less before bedtime. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Table 3. Effect on the likelihood of using mobile phone less and agreement with the statement that sleep is important to function optimally (ordinal logit regressions)

	(1) Optimal	(2) Optimal	(3) Optimal	(4) Optimal
Information	−0.173	−0.125	−0.140	−0.154
	(0.172)	(0.178)	(0.189)	(0.182)
Mobile Use	0.267	0.341	0.279	0.300
	(0.177)	(0.183)	(0.195)	(0.187)
Relaxation	0.046	0.036	−0.006	0.030
	(0.174)	(0.180)	(0.192)	(0.185)
Pseudo R^2	0.001	0.003	0.066	0.151
Observations	1,072	1,060	1,060	1,060
Control demo	No	Yes	Yes	Yes
Control habits	No	No	Yes	No
Control habits and reasons	No	No	No	Yes

Notes: The table reports coefficient estimates from ordinal logit regressions. Robust standard errors are reported in parentheses. Control demo includes gender, age, and education. Control habits includes difficulty putting the mobile phone away, satisfaction with sleep, taking active steps to achieve better sleep, pace of daily life, talking to networks about sleep, seeking confirmation, being structured, and trust in research. Control habits and reasons additionally include self-reported reasons for poor sleep and the desire to use the mobile phone less before bedtime. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Willingness to use resources improve sleep

Figure 14 shows how willing respondents were to use resources (time, money, effort, and learning) to improve their sleep. Nonparametric tests confirm the absence of differences between the treatment groups and the reference group (Chi2(12) = 12.7555, p = 0.387). The same picture arises from Column 3 of Table 1.

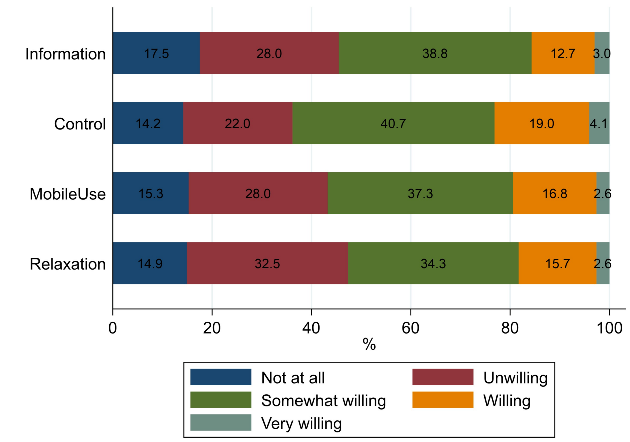

Figure 14. Willingness to use resources to achieve better sleep across groups

Table 4 shows the results for the effect of behavioral interventions on willingness to use resources to achieve better sleep with ordinal logit regression, adding controls. When we control for existing sleep and mobile phone habits (Column 3) and habits and reasons for poor sleep (Column 4), all behavioral interventions have a significant negative effect on the willingness to use resources compared with respondents who did not receive any treatment. This confirms the result from Table 1 of a possible "backfire effect". Again, we find no support for H1, H2 and H3.

Controlling for respondent's mobile phone and sleep habits, we observe that those who rarely took active steps were less inclined to use resources compared with those who took active steps. Individuals who talked about sleep within their network were more likely to use resources compared with those who rarely talked about their sleep habits. Respondents who were more organized were also more willing to make more proactive choices to achieve better sleep.

Looking now at the effects of behavioral interventions on the agreement with the statement that having enough sleep is a priority in the future (Column 4 of Table 1), again the results are not statistically significant. The same occurs when we add controls in Table 5. Again, we do not find support for H1 and H3. We do however observe some heterogeneity effects that could offer support for a self-control hypothesis (H2).[13] We observe that individuals who report always engaging in sleep-improving activities already place a high priority on sleep, whereas those who engage in such activities less frequently report substantially lower prioritization. Consistent with this pattern, we see that the effect of the Relaxation treatment is negligible or slightly negative among those who take active steps, but positive and increasing among those who rarely or never take active steps to improve sleep. Among individuals who never take active steps, the Relaxation treatment shifts some probability mass toward higher outcome categories. This heterogeneity could be consistent with differences in self-regulation or habit formation: individuals who already prioritize sleep may have little scope for further improvement, while interventions – particularly focus relaxation techniques – may lower the cognitive or self-control costs of prioritizing sleep among those with weaker baseline routines.[14]

Motivation to change existing habits to achieve better sleep quality

With regard to how motivated respondents were to change existing habits to achieve better sleep quality and to recommend relaxation techniques to people with sleeping problems, we again observe few differences across treatment groups and the reference group (Chi2(12), p=0.534). See Columns 5 and 6 of Table 1 and Table 6 and Table 7, with ordinal logit regressions, adding controls. Results with controls once more do not change the main picture. This means that again, we do not find support for H1, H2 and H3.

Exploring correlations, we find that motivation to change habits is associated with how difficult respondents thought it was to use their mobile phone less; individuals who believed it was easy to put their mobile phone away before bedtime were more motivated to change their habits. Individuals who took active steps to achieve better sleep were often more motivated to change existing habits compared with those who never took active steps.

Motivation to change existing habits is also associated with respondents' willingness to use resources to achieve better sleep quality. Among those who were not willing to use resources to achieve better sleep, 18 percent responded that they were motivated to change their habits. Among those who were willing to spend resources on having better sleep, 73 percent responded that they were motivated to change the mobile phone habits. We also consider which habits the respondents wanted to adopt first. Among the youngest respondents, 49 percent were motivated to use their mobile phone less, 43 percent of those aged 25–39-years thought similarly along with 31 percent of those aged 40–54 years. Motivation to reduce mobile phone use was linked to the respondent's current sleep quality. Among those who were satisfied with their sleep quality, 32 percent said they wanted to use the mobile phone less, whereas 56 percent of those who were not satisfied with their sleep quality wanted the same.

[13] As suggested by a referee, we examined whether treatment effects vary across other background characteristics (e.g., satisfaction with current sleep quality, age, reasons for valuing sleep and baseline activity levels). We did this by jointly testing the corresponding interaction terms. These tests provide no evidence of meaningful heterogeneity in treatment effects. We therefore do not explore this further.

[14] See more details in Tables A7, A8 and A9 as well Figures A1, A2 and A3 in the Appendix.

Table 4. Effect on willingness to use resources to improve sleep habits (ordinal logit regression)

	(1) Resources	(2) Resources	(3) Resources	(4) Resources
Information	−0.390*	−0.346*	−0.348*	−0.347*
	(0.157)	(0.160)	(0.166)	(0.168)
Mobile Use	−0.248	−0.200	−0.307	−0.356*
	(0.157)	(0.159)	(0.167)	(0.169)
Relaxation	−0.349*	−0.333*	−0.320	−0.339*
	(0.157)	(0.159)	(0.166)	(0.169)
Pseudo R^2	0.002	0.009	0.129	0.147
Observations	1,072	1,060	1,060	1,060
Control demo	No	Yes	Yes	Yes
Control habits	No	No	Yes	Yes
Control habits and reasons	No	No	No	Yes

Notes: The table reports coefficient estimates from ordinal logit regressions. Robust standard errors are reported in parentheses. Control demo includes gender, age, and education. Control habits includes difficulty putting the mobile phone away, satisfaction with sleep, taking active steps to improve sleep, pace of daily life, talking to networks about sleep, seeking confirmation, being structured, and trust in research. Control habits and reasons additionally include self-reported reasons for poor sleep and the desire to use the mobile phone less before bedtime. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Table 5. Effect on agreement with the statement that having enough sleep is a priority in the future (ordinal logit regression)

	(1) Priority	(2) Priority	(3) Priority	(4) Priority
Information	−0.017	0.013	−0.012	−0.014
	(0.163)	(0.167)	(0.172)	(0.173)
Mobile Use	−0.089	−0.034	−0.136	−0.147
	(0.164)	(0.167)	(0.173)	(0.175)
Relaxation	−0.009	−0.028	−0.034	−0.023
	(0.162)	(0.165)	(0.172)	(0.175)
Pseudo R^2	0.000	0.015	0.087	0.094
Observations	1,072	1,060	1,060	1,060
Control demo	No	Yes	Yes	Yes
Control attitudes	No	No	Yes	Yes
Control habits	No	No	No	Yes

Notes: The table reports coefficient estimates from ordinal logit regressions. Robust standard errors are reported in parentheses. Control demo includes gender, age, and education. Control attitudes include attitudinal measures related to sleep. Control habits include difficulty putting the mobile phone away, satisfaction with sleep, taking active steps to improve sleep, pace of daily life, talking to networks about sleep, seeking confirmation, being structured, and trust in research. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Table 6. Effect on willingness to recommend (ordinal logit regressions)

	(1) Recommend	(2) Recommend	(3) Recommend	(4) Recommend
Information	−0.213	−0.165	−0.131	−0.152
	(0.154)	(0.157)	(0.160)	(0.161)
Mobile Use	−0.210	−0.142	−0.187	−0.234
	(0.154)	(0.156)	(0.159)	(0.161)
Relaxation	−0.024	0.005	0.030	−0.009
	(0.154)	(0.156)	(0.161)	(0.163)
Pseudo R^2	0.001	0.011	0.049	0.056
Observations	1,072	1,060	1,060	1,060
Control demo	No	Yes	Yes	Yes
Control habits	No	No	Yes	Yes
Control habits and attitudes	No	No	No	Yes

Notes: The table reports coefficient estimates from ordinal logit regressions. Robust standard errors are reported in parentheses. Control demo includes gender, age, and education. Control habits include difficulty putting the mobile phone away, satisfaction with sleep, taking active steps to improve sleep, pace of daily life, talking to networks about sleep, seeking confirmation, being structured, and trust in research. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Table 7. Effect on motivation to change habits (ordinal logit regressions)

	(1) Motivation	(2) Motivation	(3) Motivation	(4) Motivation
Information	0.138	0.181	0.164	0.149
	(0.167)	(0.170)	(0.178)	(0.182)
Mobile Use	0.011	0.080	−0.036	−0.091
	(0.167)	(0.169)	(0.178)	(0.182)
Relaxation	−0.177	−0.159	−0.235	−0.207
	(0.168)	(0.170)	(0.177)	(0.182)
Pseudo R^2	0.002	0.008	0.100	0.130
Observations	1,072	1,060	1,060	1,060
Control demo	No	Yes	Yes	Yes
Control habits	No	No	Yes	Yes
Control habits and attitudes	No	No	No	Yes

Notes: The table reports coefficient estimates from ordinal logit regressions. Robust standard errors are reported in parentheses. Control demo includes gender, age, and education. Control habits include difficulty putting the mobile phone away, satisfaction with sleep, taking active steps to improve sleep, pace of daily life, talking to networks about sleep, seeking confirmation, being structured, and trust in research. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Sixty-one percent of those aged 18–24 years wanted to begin by correcting their circadian rhythm, whereas 41 percent of those aged 25–39 years wanted the same. Approximately 18 percent of those aged 18–24 years, 12 percent of those aged 25–39 years, and 12 percent of those aged 40–54 years wanted to use soundtracks for meditation/relaxation. Few respondents, across age groups, were motivated to start with guided relaxation.

As a summary of results, we see that we do not find support for the three main hypothesis in our study. First, we do not find that the behavioral interventions reduced the intention to reduce mobile phone before sleep to promote better sleeping habits (H1). Second, we do not find that those that were better at tackling self-control problems had better outcomes (H2). Third, we also do not find any effects of addiction, which might indicate that addiction in mobile phone use is quite widespread (H3).

Analysis of Open-ended Questions

In Table A2 in the Appendix, we present some randomly drawn quotes to illustrate what respondents wrote in the Reflection Relaxation and Reflection Mobile Use groups. In this section, we analyze the content from the reflection treatments. Recall that subjects in one treatment condition were asked to write at least three positive effects they believed they could obtain from reducing screen time. In another treatment condition, they were asked to write three positive effects they think they could obtain from relaxation techniques. We employed a Large language model to assist with the initial structuring of responses, followed by researcher-led subjective systematization.

Reflection treatment

Although both treatments prompted respondents to reflect on themes related to sleep, stress reduction, and wellbeing, the content of these reflections differed in systematic ways. Table 8 shows common themes. Reflections on reducing mobile phone use were predominantly framed around removing external stimuli, such as blue light, notifications, and cognitive overload, and were linked to expectations of calmer evenings, fewer distractions, and improved social presence.

By contrast, reflections on relaxation techniques centered on actively producing internal calm through breathing exercises, muscle relaxation, and cognitive grounding. Thus, while both treatments concerned evening routines, the former emphasized sensory relief and digital boundaries, whereas the latter emphasized bodily relaxation, emotional regulation, and internally oriented mental processes. These patterns suggest that the two prompts may engage related but psychologically distinct mechanisms for improving rest and evening well-being.

Across both treatments, however, reflections tended to be descriptive rather than motivational. Respondents articulated what the behaviors could lead to, consistent with the prompt they received, but rarely expressed concrete intentions or actionable strategies. As a result, qualitative evidence gives limited indication that either form of reflection is sufficient to generate meaningful behavioral change on its own. Reflection can increase awareness, but sustained changes in behavior typically require more structured commitment devices, such as goal-setting, planning prompts, reminders, or forms of social accountability.

A potentially more effective intervention design would therefore shift from asking respondents to reflect on hypothetical benefits to asking them to identify three specific actions they intend to try, thereby transforming a reflective exercise into an intention-formation prompt with a clearer behavioral pathway.

Self-reported habit changes

Finally, after exposure to treatment, we asked subjects a follow-up question to the initial question "To what extent do you want to establish better sleep habits?".

We analyzed 105 text-responses of the concrete actions respondents wanted to take. We observe that a substantial subgroup stated that they had no need for changes, either because they were satisfied with their current routines or perceived sleep problems as unrelated to behavior. Others emphasized medical or pain-related constraints. Many respondents pointed out reduce stimulating activities in the evening, such as screen use, caffeine, or late meals, as possible strategies for improving sleep. A smaller but notable group mentioned internal relaxation practices such as yoga or breathing exercises. Finally, some responses were brief, ambiguous, or indicated a lack of ideas, making them less suitable for text-analysis.

Discussion of results, Policy implications and Limitations of the Study

In this section we further discuss our main result, the null effect of behavioral interventions, the policy implications of this result and the limitations of our study.

Discussion of Null Results

Given the null results, it is of interest to discuss some potential mechanisms for this. We believe that there are mainly two mechanisms.

The first mechanism is that mobile phone use is an ingrained habit and, for some people, even an addiction, which makes it more challenging to tackle self-control problems (hypotheses 2 and 3). In these cases, behavioral interventions that leave the final decision to individuals are less likely to have an effect. If phone use before bed is indeed habitual or addictive, as suggested by our results, then light-touch interventions – especially those that rely on rational deliberation – are unlikely to produce meaningful change. Note that this is not just a limitation of the specific behavioral interventions tested, but as a broader structural mismatch between the intervention type and the behavioral problem. We can think for example of addiction in other contexts, like tobacco. The fact that an information campaign has little effect on tobacco consumption is not necessarily because of a problem with the information campaign. People who smoke can rationally understand that tobacco is bad for them, and would even be

Table 8. Qualitative themes reported for Q19 and Q20

Theme	Q19: Reducing Mobile Use Before Bed	Q20: Relaxation Techniques
Sleep improvements	Very common: faster sleep onset, deeper sleep, longer sleep, more rested mornings.	Very common: easier sleep onset, deeper and more continuous sleep, fewer awakenings.
Stress reduction and mental calm	Reduced mental stimulation, less rumination, calmer mind due to fewer impressions.	Strong emphasis on lowering pulse, reducing tension, calming thoughts, and emotional regulation.
Bodily relaxation / physical effects	Relief for eyes (less blue light), relaxed neck and shoulders, reduced physical strain.	Muscle release, reduced headaches, improved breathing, parasympathetic activation, lower blood pressure and pulse.
Cognitive regulation	Less mental overload, fewer distractions, reduced digital impulses.	Clearing the mind, shifting attention away from worries, positive thought patterns, mental grounding.
Social benefits / interpersonal presence	More time with partner or family, improved conversations, greater social presence.	Minimal emphasis; relaxation described mostly as an individual practice.
Alternative activities	Reading, hobbies, reflection, non-digital evening routines.	Music, audiobooks, meditation, breathing exercises, warm showers, physical movement.
Daily routines / structure	Earlier bedtime, better morning energy, more consistent routines.	Establishing bedtime rituals, body preparing for sleep, transitioning into rest.
Reducing external stimuli / dependence	Less availability, fewer notifications, digital boundaries, avoiding work e-mail.	Less often mentioned; focus on internal calm rather than external restriction.
Emotional wellbeing	Some references to reduced stress and better mood.	Frequent references to emotional regulation, calmness, inner peace, and positive feelings.
No effect / uncertainty	Some respondents report no benefit or already low screen use.	Some respondents report no effect or no need, often because they already sleep well.

willing to consider quitting, but the habit is stronger than the will. In these cases, strong measures would be needed, from age prohibitions so that younger people do not gain a habit from early age to medical treatment of those already addicted. All this indicates that similar measures might be needed in the first place for mobile phone use habits.

The second mechanism is that there are several reasons for people having bad sleeping habits, and people might believe that changing mobile phone use habits is not enough to achieve better sleeping routines. This might explain why the behavioral intervention in Hoong (2021) worked for social media use but not in our study, since here we have both mobile phone use and sleep habits. In Hoong (2021) there is a direct connection between the behavioral intervention used and outcome variable (social media use). In our study, instead the outcome variable is sleep and the behavioral interventions focus on mobile phone use. Besides in our study, the behavioral interventions target total mobile phone use, while in Hoong (2021) it is more limited since it just focused on social media use. This means that in Hoong (2021) subjects can substitute social media use by other apps in the mobile phone, but not in our study (in our study they can only substitute for other electronic devices).

Policy Recommendations

As already briefly discussed above, mobile phone policies in many countries have so far had a more hands-off approach. Until now, the norm has been to leave to individual schools if they should have some type of intervention (bans or other interventions) to reduce the use of the mobile phone. In addition, politicians have preferred not to go beyond mobile phone policies that give general advice, i.e., that do not restrict the freedom of people. Part of the reason for this preference is not only that advice (and similar behavioral interventions that do not restrict freedom) are less invasive and therefore respect more individual freedom, but also because they are cheaper and easier to implement than restrictions or bans. Another reason has been the intensive lobbying by social media companies both in Washington and Brussels.

However, our results show that behavioral interventions that give the last word to people might not work in terms of the interactions between self-reported mobile phone use and better sleeping habits. In this sense, these “light” behavioral interventions, despite being cheaper and easier to implement, might not be effective, because they run the risk to not deliver the desired outcomes. This is mostly because mobile phone use is an ingrained habit that turns often into an addiction. With ingrained habits and addiction problems, behavioral interventions that leave lots of freedom to people look to have very reduced power. This seems to indicate that politicians should try other approaches that are more invasive of peoples' choices, like restrictions and bans.

In the last year or so, the general tide against restrictions and bans has however started to change, especially when it concerns young children and social media. For instance, some countries have started to introduce age limits for social media, with the age varying by country and some requiring parental consent for younger users. For example, Australia has banned access for those under 16, while countries like Denmark, France, and Norway are moving towards an age limit of 15. In turn, the EU is backing a proposal that children should be at least 16 to access social media. Similarly, restrictions and bans on young people's mobile phone use in schools are also increasing. This has been the case in countries like France, Belgium, and certain US states. It is, however difficult to get a general overview on school bans on the us of the mobile phone since this can vary from school to school even in the same country.

Another issue is that restrictions and bans might be circumvented. For example, as mentioned before some parents want to be in contact with their children all the time, due to fearing for their security (attacks with guns in schools in the US are a known problem). Even if parents agree with it, it is not easy to have a technological solution that prevents children access to social media.

Moreover, as we also have discussed above, restrictions and bans also have some challenges in that individuals can opt-out and/or substitute the use of the mobile phone by other electronic devices, like laptops and game consoles. Then it is also not clear that restrictions and bans can be effective. So further research needs to be done to look at restrictions and bans in the interaction between mobile phone use and sleeping habits.

Limitations of the Study

One limitation of this study is that we use self-reported data, which can lead to response bias. There can be several reasons for response bias in self-reported data; see for instance Rosenman et al. (2011). First, subjects can fail to understand the questions. Second, subjects might not have accurate memory of what is asked. Third, subjects might wish to give a good impression of themselves in the survey, often called social-desirability bias. Fourth, related to the previous point, the setting where the survey is done can also affect responses. For example, at school, at home, in a lab, or on your private computer or mobile phone can give subjects different feelings of privacy and/or ease of being truthful.

Regarding the above, we can say the following. First, we have not found comprehension issues during the experiment and subjects seemed to reply consistently across questions. Furthermore, subjects within age groups showed similar response patterns in the different questions. Second, memory can of course always be an issue, but we have asked about recent behavior, which other studies have shown that minimizes the memory problem; see Koller et al. (2023). Third, regarding social-desirability bias, the responses given our study for sleeping habits conforms to those given in other surveys with the Norwegian population; see Norwegian Institute of Public Health (2022). In addition, the picture that arises from our results is not that rosy, in the sense that it shows a problem with sleeping habits and mobile phone use. Therefore, it does not look like the subjects tried to give a better picture of their sleeping and mobile phone use habits. Finally, concerning the last point, the setting where the survey was done, the survey was done on the subjects' private computers and/or private mobile phone, where they are exposed to less severe privacy issues and less fear that someone can see their answers apart from the researchers.

Another point is that it is challenging to do sleep research not based on self-reported data, since these implies coming into the inside subjects' private life and following them for some time, which raises concerns of privacy and cost-effectiveness. In fact, most sleep studies are based on self-reported data; see Gradisar et al. (2011); Kessler et al. (2011); Taylor et al. (2011); Hoong (2021); Bartel et al. (2019); He et al. (2020); Sohn et al. (2021). It is of course possible to have more control of the data if we study subjects, for example in a sleeping clinic, but this takes subjects out of their natural environment. Another way would be for instance to develop an app that follows subjects' sleep. Even in this case, however, subjects could try to manipulate the results. In the context of our study, the use of an app to monitor sleep would mean that we would be also affecting the other variable in our study, mobile phone use. There are also reasons to believe that the self-selection problem can be higher in more invasive experiments than in less invasive experiments; see Collis and Eggers (2019), i.e. the interventions that protect more subjects' privacy, as is the case with self-reported data. Accordingly, self-selection in more invasive interventions can go both ways. For example, those with sleep problems might fear more invasive interventions because they are going to be tracked so closely; or alternatively can promote them to sign-up hoping to solve their sleeping problems.

Note also that the same problems arise with mobile phone use studies based on self-reported data. Again, here most of the studies are with self-reported data; see the review by James et al. (2023). Part of the reason for this is that subjects need to allow researchers for instance to access their log of mobile phone use, and potentially also content and app usage, and this can again raise issues in terms of privacy. Another issue, as mentioned above for the sleep studies, is that in more invasive interventions subjects even so manipulate their mobile phone behavior. For example, instead of using the mobile phone to check social media, they can use a computer. In the same way as mentioned above, subjects might opt out of the study, leading again to a problem of self-selection. For example, Bartel et al. (2019) report that only 26% of their sample opted in in using an app that monitors their phone usage.

Finally, another issue with self-reported data is that it can lead to an intention-behavior gap. Accordingly, subjects might have the intention to change the mobile phone use but, in the end, they do not do it. The same can occur with intention of changing sleeping habits that do not materialize.[15] The null results indicate, in our view, that this is probably not the case in this study. In other words, if subjects have no intention of changing their habits—either their sleeping habits or their mobile phone use—then they are unlikely to do so. In any case, the intention-behavior gap points out the need for future research that prioritizes the inclusion of objective behavioral data (e.g., digital tracking, app usage, or sleep monitoring) to validate and complement self-reports, especially because as indicated above many studies in this field look only at self-reported data.

Discussion

In this paper, we have: (i) mapped the sleep and mobile phone use habits among a representative sample of the Norwegian population, and (ii) tested the effects of three different behavioral interventions on sleep and mobile phone use habits.

The results show that the proportion of respondents who thought that the mobile phone was addictive is greatest among the youngest respondents. It is also the youngest respondents who believed it was the most difficult to put away the mobile phone before bedtime (79 percent). In comparison with the oldest respondents, the youngest put the mobile phone away just before going to bed. Likewise, we observe that the youngest had a greater desire to use the mobile phone less before bedtime (64 percent) compared with older respondents.

In turn, we find that the behavioral interventions used in this study had little or no effect on intentions to change behavior and habits (hypothesis 1). In this sense, behavioral interventions did not manage to solve self-control problems (hypothesis 2), which indicates that most subjects in our sample struggle with either strong habits and/or addiction associated with the use of the mobile phone (hypothesis 3).

This shows that behavioral interventions that leave a lot of freedom to subjects in their choices, like the ones used in this study, may have little policy potential to change sleep and mobile phone habits. Instead, other types of measures, which leave less freedom to subjects in their choices, are needed for a stronger commitment effect on behavioral changes. Examples of some of these tools are objectives and planning nudges: respondents identify their goals and are then reminded of the goals they had set. This type of behavior can assist individuals in achieving goals through what is referred to as the "Theory of Planned Behavior" (Ajzen, 1991). Several studies that combine these components have used, for example, journaling or digital tools to help individuals achieve their goals (Bartel et al., 2019). If, in the end, these nudges also fail to reduce mobile phone use, we would need to test more invasive measures such as restricting or banning the use of the mobile phone, for instance after a certain hour. One example could be a kind of reverse alarm clock, i.e. a sleeping-hour alarm clock, where the individual can choose when the mobile phone enters hibernation mode and cannot be used after a certain pre-defined hour in the evening. A more extreme case would be for authorities to forbid young people to use social media before they reach a certain age. Another alternative is to restrict mobile phone use during schooling time. As discussed above, these two measures have been starting to be discussed in some countries.

Despite this, we have some results that can give some clues for future research. For example, respondents' baseline behavior seems to be relevant; the effect of the Relaxation treatment seems to differ between those who always take active steps to improve sleep at baseline compared to those who never take such steps. In addition, respondents who rarely took active steps to achieve better sleep were less willing to use resources (e.g, time, learning, and money) to achieve better sleep compared with those who always took active steps. We also found that more organized individuals were more willing to use resources to achieve better sleep.

[15] The intention-behavior gap also makes it more problematic to make claims about causality, since change in intention might not conduce to real changes in behavior.

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Appendix

Number of participants treatment conditions

Table A1. Number of Participants in Each Treatment Condition

Treatment Condition	Number of Subjects
Information	268
Mobile use	268
Relaxation	268
Control	268

Responses Reflection Relaxation and Reflection Mobile Use

Here (Table A2), we present some randomly drawn quotes to illustrate what respondents wrote in the Reflection Relaxation and Reflection Mobile Use groups. When respondents were asked to reflect on three positive effects related to relaxation, most mentioned better sleep, more calmness of the body, fewer thoughts, and less stress. Respondents who were asked to reflect on three positive effects related to reduced screen time mentioned less stress and fewer troubling thoughts and disturbances. Better sleep and falling asleep more easily were mentioned as other positive effects. Some mentioned few or no positive effects of reduced screen time and relaxation techniques.

Information about the Norstat Panel

Norstat is a market-research company that offers a panel of consumers who can be invited to participate in surveys, tests, and other studies. Panel members receive invitations to take

Table A2. Perceived effects of reflection/relaxation and reduced mobile use

Reflection Relaxation	Reflection Mobile Use
Calmer body, less stress, and calmer thoughts.	Falling asleep faster, better sleep, and less stress.
Relaxed shoulders, calmer pulse, fewer headaches.	Fewer disturbances, improved ability to fall asleep, and lower resting heart rate.
Makes you tired, facilitates falling asleep, helps reduce mobile phone addiction.	Better social life, more time outdoors, and being disconnected.
Peace of mind and stress reduction.	Falling asleep faster, deeper sleep, and improved sleep quality.
Music, meditation, and breathing exercises.	Screen viewing is not the cause of my sleep problems.
Calmness, clearer thoughts, and tension release.	Protect eyesight, improved peace of mind, and better sleep.
Shifts focus, calms the mind, and relaxes the body.	Reduced social media use; less pressure to read and respond to work emails; reading books or magazines.
Meditation, audiobooks, and podcasts.	Limited screen time; phone used mainly for calls and email.
Muscle relaxation, improved sleep, and better digestion.	Less exposure to light, fewer headaches, and time to reflect on the day.
No effect on sleep quality.	Reading more, better sleep, and preparation for the next day.
Breathing exercises, music, and reading.	More sleep, more personal time, and more time for homework.
Sleep aid, muscle relaxation, and fewer intrusive thoughts.	Improved sleep, mental health, and social life.
Inner peace, positive thoughts, and muscle relaxation.	Reduced screen time, lower availability, and using an alarm clock.

part in surveys (online, via an app or web), and sometimes other research tasks (e.g., focus-groups, product tests, phone interviews) depending on the study. When completing a survey, you are rewarded – typically with "Norstat coins" (and sometimes "stars" for activity/loyalty). These coins can be exchanged for gift cards, vouchers, or sometimes charitable donations.

Norstat uses profiling of its panel members (demographics, region, age, etc.) so they can recruit respondents that match a target group. For example, if you want a survey that reflects the general Norwegian population by gender, age and region, Norstat can draw a representative sample from its panel. The participants for this survey experiment were randomly selected from Norstat's panel, with quotas for gender, age groups, and regions to reflect the Norwegian population on these observable covariates.

OLS regressions

Table A3. Effect on Outcome Variables (OLS)

	(1) Use less	(2) Optimal	(3) Resources	(4) Priority	(5) Recommend	(6) Motivation
Information	0.123	-0.034	-0.213*	0.022	-0.131	0.067
	(0.096)	(0.060)	(0.089)	(0.069)	(0.101)	(0.070)
Mobile Use	0.108	0.104	-0.134	-0.034	-0.134	0.015
	(0.094)	(0.056)	(0.089)	(0.072)	(0.100)	(0.069)
Relaxation	0.123	0.022	-0.183**	0.019	-0.022	-0.045
	(0.095)	(0.061)	(0.089)	(0.068)	(0.100)	(0.068)
Constant	2.687**	4.504**	2.769**	3.593**	2.772**	3.310**
	(0.067)	(0.044)	(0.064)	(0.051)	(0.070)	(0.051)
Observations	1072	1072	1072	1072	1072	1072
R^2	0.002	0.006	0.006	0.001	0.003	0.003

Note: The table reports OLS estimates from regressions without controls with robust standard errors in parentheses. Use less: desire to use the mobile phone less before bedtime in the coming week. Optimal: agreement that sleep is important to function optimally in daily life. Resources: willingness to use resources to achieve better sleep. Priority: priority to obtain enough sleep in the coming time. Recommend: willingness to recommend relaxation techniques to others. Motivation: motivated to change existing habits. $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

Table A4. Effect on the likelihood of using mobile phone less (Columns 1-3) and agreement with the statement that sleep is important to function optimally (Column 4-6) (OLS) with controls

	(1) Likely	(2) Likely	(3) Likely	(4) Optimal	(5) Optimal	(6) Optimal
Information	0.123	0.134	0.114	-0.034	-0.023	-0.026
	(0.096)	(0.097)	(0.090)	(0.060)	(0.060)	(0.059)
Mobile Use	0.108	0.112	0.100	0.104	0.121*	0.099
	(0.094)	(0.095)	(0.088)	(0.056)	(0.055)	(0.055)
Relaxation	0.123	0.134	0.130	0.022	0.017	-0.001
	(0.095)	(0.096)	(0.091)	(0.061)	(0.060)	(0.060)
Constant	2.687**	2.701**	0.931	4.504**	4.226**	4.556**
	(0.067)	(0.122)	(0.556)	(0.044)	(0.084)	(0.296)
Observations	1072	1060	1060	1072	1060	1060
Control demo	No	Yes	Yes	No	Yes	Yes
Control habits	No	No	Yes	No	No	Yes
R^2	0.002	0.008	0.172	0.006	0.048	0.140

Note: The table reports estimates from OLS regressions with robust standard errors in parentheses. Control demo = gender, age, and education. Control habits = difficult to put the mobile away, satisfied with sleep, takes active steps to achieve better sleep, pace of daily life, talks to networks about sleep, seeks confirmation, is structured, and trusts research. $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

Table A5. Effect on willingness to use resources to achieve better sleep and agreement with the statement that having enough sleep is a priority in the future (OLS)

	(1) Resources	(2) Resources	(3) Resources	(4) Priority	(5) Priority	(6) Priority
Information	-0.213*	-0.182*	-0.163*	0.022	0.032	0.020
	(0.089)	(0.090)	(0.079)	(0.069)	(0.068)	(0.064)
Mobile Use	-0.134	-0.093	-0.141	-0.034	-0.017	-0.069
	(0.089)	(0.090)	(0.080)	(0.072)	(0.071)	(0.068)
Relaxation	-0.183*	-0.166	-0.168*	0.019	0.012	0.009
	(0.089)	(0.088)	(0.077)	(0.068)	(0.067)	(0.064)
Constant	2.769**	2.700**	1.343*	3.593**	3.416**	3.613**
	(0.064)	(0.108)	(0.544)	(0.051)	(0.086)	(0.314)
Observations	1072	1060	1060	1072	1060	1060
Control demo	No	Yes	Yes	No	Yes	Yes
Control habits	No	No	Yes	No	No	Yes
R^2	0.006	0.026	0.295	0.001	0.034	0.177

Note: The table reports estimates from OLS regressions with robust standard errors in parentheses. Control demo = gender, age, and education. Control habits = difficult to put the mobile away, satisfied with sleep, takes active steps to achieve better sleep, pace in daily life, talks to networks about sleep, seeks confirmation, is structured, and trusts research. $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

Table A6. Effect on willingness to recommend and motivation (OLS)

	(1) Recommend	(2) Recommend	(3) Recommend	(4) Motivation	(5) Motivation	(6) Motivation
Information	-0.131	-0.095	-0.085	0.067	0.084	0.072
	(0.101)	(0.101)	(0.097)	(0.070)	(0.071)	(0.066)
Mobile Use	-0.134	-0.091	-0.119	0.015	0.038	-0.007
	(0.100)	(0.099)	(0.096)	(0.069)	(0.070)	(0.067)
Relaxation	-0.022	-0.003	0.011	-0.045	-0.040	-0.046
	(0.100)	(0.101)	(0.098)	(0.068)	(0.068)	(0.064)
Constant	2.772**	2.657**	1.939**	3.310**	3.229**	2.904**
	(0.070)	(0.117)	(0.615)	(0.051)	(0.087)	(0.365)
Observations	1072	1060	1060	1072	1060	1060
Control demo	No	Yes	Yes	No	Yes	Yes
Control habits	No	No	Yes	No	No	Yes
Adjusted R^2	-0.000	0.024	0.096	-0.000	0.009	0.142

Note: The table reports estimates from OLS regressions with robust standard errors in parentheses. Control demo = gender, age, and education. Control habits = difficult to put the mobile away, satisfied with sleep, takes active steps to achieve better sleep, pace of daily life, talks to networks about sleep, seeks confirmation, is structured, and trusts research. $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

Heterogeneity

We explore whether the treatment effect differs based on subjects' responses to questions about reason that sleep is important to them, satisfaction with current sleep quality and baseline engagement in sleep-improving activities. We are conducting Likelihood ratio tests that examine the null-hypothesis that all interaction terms are jointly equal to zero. The alternative hypothesis that at least one interaction term is non-zero. The test does not say which treatment drives the heterogeneity and which activity level shows the effect. We explore the directional effects in cases where the LR test indicates heterogeneous effects.

Reasons that sleep is important

Likelihood-ratio tests (Table A7) comparing ordered logit models with and without interaction terms provide no evidence of treatment effect heterogeneity by respondents stated reason for valuing sleep for any of the outcomes (all p-values larger than 0.12).

Table A7. Results from LR test of model with and without interaction term between treatments and importance of sleep

Outcome	LR χ^2	p-value
Likely	17.7	0.126
Priority	10.2	0.598
Optimal	5.22	0.950
Resources	12.2	0.433
Advice	8.21	0.769
Motivation	12.9	0.373

Satisfaction with current sleep quality

Likelihood-ratio tests (Table A8) comparing ordered logit models with and without interaction terms provide no evidence of treatment effect heterogeneity by respondents stated satisfaction of currently sleep quality for any of the outcomes (all p-values larger than 0.10).

Table A8. Results from LR test of model with and without interaction term between treatments and satisfaction of current sleep

Outcome	LR χ^2	p-value
Likely	9.88	0.626
Priority	13.3	0.345
Optimal	8.03	0.783
Resources	10.2	0.600
Advice	6.41	0.894
Motivation	14.3	0.283

Baseline engagement in sleep-improving activities

We explore whether the treatments affect outcomes variables differently for people who already take many vs. few active steps to achieve good sleep. Likelihood-ratio (Table A9) tests comparing ordered logit models with and without interaction terms provide evidence of treatment effect heterogeneity for prioritizing enough sleep in the coming time.

Table A9. Results from LR test of model with and without interaction-term between treatments and baseline engagement in sleep-improving activities

Outcome	LR χ^2	p-value
Likely	11.9	0.454
Priority	27.0	0.0076
Optimal	10.3	0.594
Resources	6.05	0.914
Advice	14.6	0.264
Motivation	16.2	0.181

We further explore the details of the significant LR-test. Compared to those who always take active steps to improve sleep, people who take fewer active steps to achieve good sleep, want to prioritize sleep much less. Among people who always take active choices, the Relaxation treatment has little or negative effect. Among people who rarely or never take active steps, treatment increases self-reported sleep prioritization. Figure A1 plots the treatment–control contrasts from an ordered logit model. Estimates are differences in the model's linear predictor (log-odds index), conditional on baseline activity level, with 95% confidence intervals.

By further examining predicted probabilities (Figures A1, A2, A3), we find that the Relaxation treatment affects the distribution of sleep-priority responses differently depending on individuals' baseline sleep-improving activity. At the upper end of the distribution of the outcome variable (prioritizing sleep), the Relaxation treatment increases the probability of the highest priority category more strongly among individuals who never take active steps than among those who always take active steps.

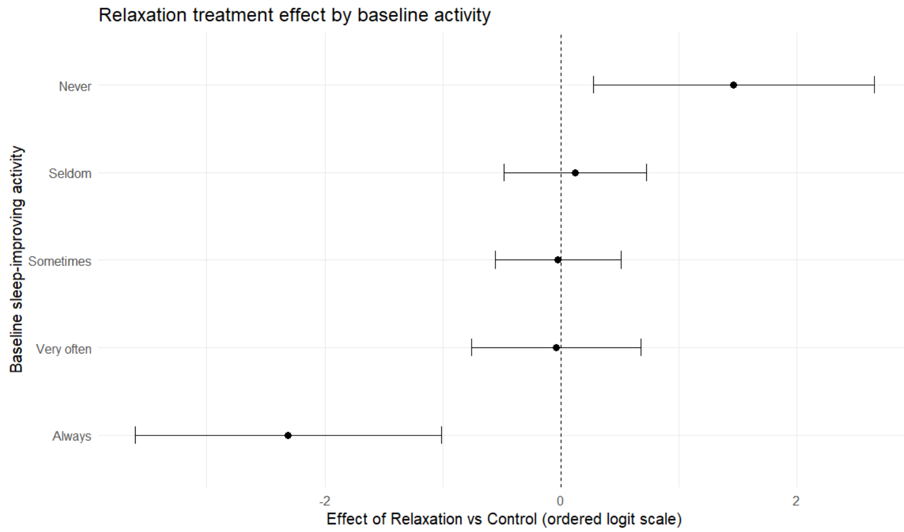

Figure A1. Treatment–control contrasts (ordered-logit scale Relaxation vs. Control)

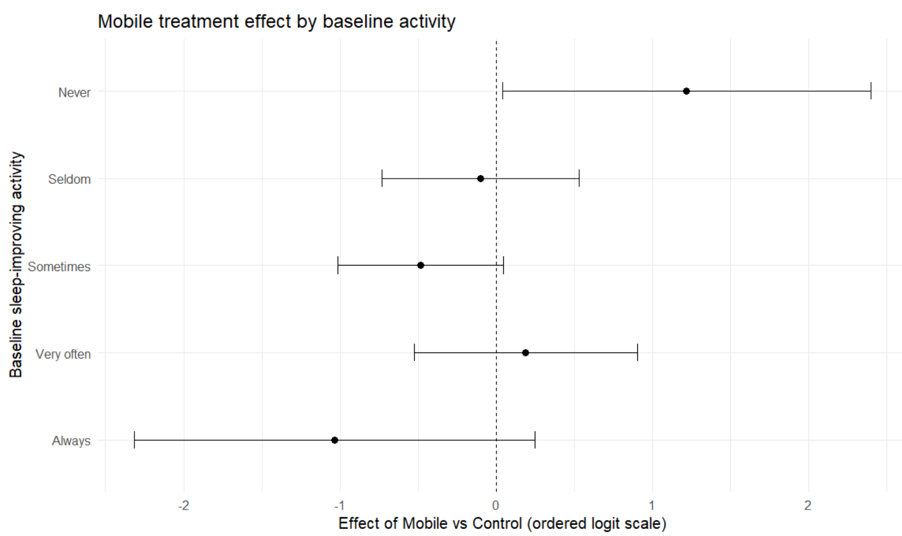

Figure A2. Treatment–control contrasts (ordered-logit scale) MobileUse vs. Control

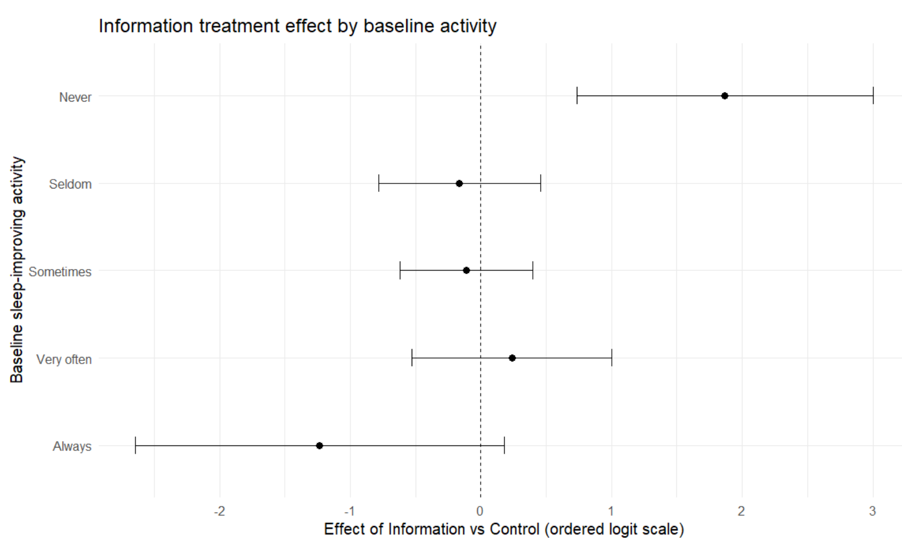

Figure A3. Treatment–control contrasts (ordered-logit scale) Information Benefit vs. Control