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Time-inconsistency, awareness and the demand for soft commitment devices in social media use

Bachelor Thesis: Economie en Bedrijfseconomie

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Abstract

This paper researches the awareness of time-inconsistency and the demand for a soft commitment device related to social media. A survey was conducted in which participants reported their predicted and ideal time on social media, and after seven days they reported their actual time on social media during this period. They also reported their opinion on the attractiveness and likelihood of use of a phone application restricting their phone and/or social media use. The results strongly suggest that being more aware of time-inconsistency increases the reported attractiveness and likelihood that a participant would use the application. This suggests that increasing awareness of time-inconsistency could make people more willing to work towards reducing it.

Introduction

For most of us, it is impossible to imagine a world without the internet. According to research done by Eurostat in 2010, The Netherlands scored the highest of all EU 27 countries (all members of the European Union), Norway, Croatia and Turkey on internet connection, with 91% of households having an internet connection, and even 99% of households with children (Eurostat, 2010). With the rise of internet use, social media has become more popular as well, especially among young people. Worldwide, Facebook is the most frequently used social media app: they started out in 2008 with around 100 million users, rising to 2.91 billion users at the start of 2022 (Statista, 2022).

Whether it is following celebrities on Twitter, discussing issues on Facebook or posting and viewing selfies on Instagram, being active on social media is an important part of many people's daily life. Social media is a fun way to communicate with friends and strangers, it can be a creative outlet and it can even be helpful and teach you something. According to Alcott, Gentzkow, & Song (2021), the average person with access to internet spends around 2.5 hours per day on social media. An increasingly popular interpretation of this rise in social media use, is that habit formation and self-control problems play a large role, which Alcott et al. (2021) calls digital addiction. Hou, Xiong, Jiang, Song, & Wang (2019) researched the influence of social media addiction on mental health and academic performance on college students, and found that many students experienced negative influences on both their mental health and academic performance due to social media addiction. Frequent social media use has also been linked to depression and other mental health problems among high school students (Pantic et al., 2012). Another element to this, is that platforms such as Netflix and YouTube, and the many other streaming services got more popular during the COVID-19 pandemic. Binge-watching has become more of a problem, with people often not realising how many hours per day they are watching (Rahman & Arif, 2021).

All of these issues relate to the concept of time-inconsistency. Time-consistency, which can also be called dynamic consistency, can be defined as follows: "Dynamic consistency in preferences between dates t and $t'>t$ arises when a person's state contingent preferences for actions taken at date t', expressed at date t, are consistent with her state contingent preferences for actions taken at date t', expressed at date t'" (Ericson & Laibson, 2019; p. 6).

This means that a person would make the same decision about something in the future, whether they decide right now or at that future moment. Dynamic inconsistency can thus be defined as follows: "Dynamic inconsistency in preferences arises if there is any pair of values t and $t'>t$, which is not characterized by dynamic consistency in preferences" (Ericson & Laibson, 2019; p. 6). Wong (2008) describes four different types of people with regards to time-consistency. First there are time-consistent people, who behave according to plan, and plan according to what is optimal in the long-run. They predict their ideal behaviour, their preference at time *t* for their actions at time *t'*, in this case meaning a set time that they would be satisfied with, not wishing any more or less. Their predicted or planned time, meaning the time they think that they will actually be spending, is equal to the ideal time, which in turn is equal to their actual time. Time-inconsistency exists when someone has an ideal, but is unable to conform to this ideal. There are three forms of time-inconsistent people. We have the naïfs, who are completely unaware of their time-inconsistency, they predict that they will follow their original and planned ideal behaviour, but end up deviating from it. Sophisticates are time-inconsistent, but aware of this. They predict that they will deviate from their ideal behaviour, and follow their prediction. Finally, there are partial naïfs, who predict a deviation from their ideal, but cannot properly estimate its severity, deviating further from their ideal plan than predicted (Wong, 2008; p. 645-646).

In this study, the concept of time-inconsistency will be researched via two main research questions. First of all: Are people time-inconsistent, and are they aware of this? Previous research showed that many people are indeed time-inconsistent. For example, in the Wong (2008) experiment, only six to seven percent of students were time-consistent. O'Donoghue & Rabin (1999) provided a model showing time-inconsistency. They primarily focus on present-bias, which is something that can lead to time-inconsistency: "When considering trade-offs between two future moments, present-biased preferences give stronger relative weight to the earlier moment as it gets closer" (O'Donoghue & Rabin; 1999, p. 103). A study by Ainslie and Haslam (1992) showed this, by showing how some people do prefer $100 today over $200 in two years, but do not prefer $100 in six years over $200 in eight years. Even though there the time between the pay-off points is the exact same, the preference changes, which confirms time-inconsistency. Namely, in six years, the situation will be the exact same as right now, but the participants would have a different presence, deviating from their initial ideal situation.

In the above example, it can be seen that some people will prioritise activities with immediate rewards and procrastinate on activities with immediate costs. This is often at the base of time-inconsistency and self-control problems. People will end up spending more time on activities that they deem fun and giving them immediate satisfaction, and less on more boring activities, or activities that cost more effort without giving immediate satisfaction. They will prefer watching a show on Netflix or scrolling through Twitter over writing a paper, so their ideal plan for tomorrow is writing the paper, while watching Netflix today. However, when tomorrow becomes today, they will still prefer to watch Netflix in the present and write the paper at a later time, and one will deviate from this previously set ideal. This is naïve behaviour, because every day, a person will keep on procrastinating something they do not want to do in favour of something more fun, since they are present-biased, ignoring the ideal. Since they are not aware of their bias and time-inconsistency, they will keep on procrastinating.

This forms the second research question: Will people who are aware of their time-inconsistency (sophisticates) be more interested in and willing to use self-control devices, such as smartphone applications that restrict the amount of time a person can spend on an app, than people who are unaware of their time-inconsistency (naïfs)? O'Donoghue & Rabin (1999) mention that sophisticated people might try to control for their time-inconsistency, as they are aware of their bias and pessimistic about their future behaviour. Knowing that they will probably be procrastinating in the future, they might be more willing to use external self-control to force themselves into not procrastinating. One way to do this, is by using a commitment device. For example, Carrera, Royer, Stehr,, Sydnor, & Taubinsky (2019) conducted an experiment with commitment contracts regarding gym attendance, in which they also controlled for participants time-inconsistency. Most participants viewed themselves as time-inconsistent as well, but were not or not fully aware of their time-inconsistency, as Cerrera et al. (2019) mention regarding the overestimation of gym attendance. Half of their participants received a so-called information treatment, in which they received information about their own past visits trying to make them more aware of their time-inconsistency. Carrera et al. (2019) then offer a commitment contract to exercise more (or less), with a financial incentive. It appeared that demand for contracts with high financial risk would decrease when participants become more aware of their time-inconsistency. This is because they are afraid that they will not be able to keep their commitment, since they did not in the past, and they will lose money. This concludes that awareness of time-inconsistency influences decision making around commitment devices, however, this could have a very different effect when using a soft commitment device without any financial burden or incentive. It has been shown that people aware of their time-inconsistency often have a strong preference for changing their future behaviour, and without fear of making a financial loss, they might be more inclined to take up a commitment device.

Sadoff & Samek (2018) describe that, even though there is a lot of research done on time-inconsistency and self-control problems, little is known about the demand for commitment devices. They conducted an experiment in which participants would receive an experience with a commitment device, limiting their food choices to healthier options. They found a significant increase in short-term healthier food choices, and when offering the participants the chance to voluntarily use the commitment device, the demand was doubled compared to pre-treatment demand. Alcott et al. (2021) conducted an experiment with incentives to reduce screentime. They determined that around 31 percent of social media use is caused by self-control problems, and showed how monetary incentives can make people limit their screentime. Finally, Hoong (2021) conducted a randomised experiment, in which participants were given encouragement to use a soft commitment device, limiting their screentime. Hoong (2021) found that participants would use their phones more than they predicted and desired, and that a soft commitment device would reduce their screentime significantly. From all of this, we can form two hypotheses:

1) A considerable portion of people will be time-inconsistent, some of whom are naïve, some partial-naïve and some sophisticated.

In all of the mentioned experiments and studies, it appeared that a large proportion of participants was time-inconsistent. Most of these studies also mentioned that a large part of these time-inconsistent participants were only somewhat or not at all aware of their time-inconsistency. Therefore, it is to be expected that a large proportion of participants will be time-inconsistent, with them being separated into different levels of awareness of this time-inconsistency.

2) People who are aware of their time-inconsistency will find a soft commitment device more attractive and will be more likely to use it.

It has been proven that awareness of time-inconsistency influences decision making around commitment devices. However, people are often afraid that they will end up worse because they cannot keep up their commitment, resulting is a financial loss. With a soft commitment device, this issue is less prevalent. The commitment is voluntary and there is no specific prize or incentive for completing or failing the commitment other than personal improvement. There could, for example, be a loss in the sense of negative feelings for not being able to keep the commitment, or for breaking a promise to a friend, but since these losses are not tangible, people might be less afraid to take them up. It will therefore be expected that participants who are aware of their time-inconsistency, and therefore, as Carrera et al. (2019) mention, their interest in bettering their personal future, would find a soft commitment device attractive and would be likely to use it.

An experiment such as Wong (2008), which researched time-inconsistency among a group of students in the same course, had a homogenous group of participants, with on average the same age and level of education. This research will contribute to the literature, as its goal is to receive responses from people with different ages and levels of education, in order to apply the results to a larger population. The research will be focused primarily on a Dutch sample. It will be combining previously done research on specifically the awareness of time-inconsistency and commitment devices, specified on social media use. There has been quite a lot of research regarding the function of commitment devices, proving that it improves behaviour regarding time-inconsistency. Knowing that commitment devices work, this study will be improving the knowledge regarding them by researching the demand for them when there is not specific financial or material burden or incentive connected to them.

Methodology

In order to address the research question and test the hypotheses, a survey was conducted. This survey was available in both English and Dutch. As previously mentioned, the sample should include a diverse group of participants with different levels of education. When conducting English surveys, there could be a language-barrier, thus possibly excluding participants with lower levels of education or less experience with the English language. Since the study is primarily focused on a Dutch sample, and in order to include everyone, the survey will include all text in both English and Dutch. All participants are asked to enter some demographic details. These are: gender, age, level of education and nationality. Both the fist and second survey can be found in Appendix B.

The survey focusses on the amount of time the participants will spend in the next week (seven days, starting the day after doing the survey) using social media. In this survey, social media is defined as follows: media technology that facilitates the sharing of ideas, thoughts and information through the building of virtual networks and communities. Examples of such media are Facebook, Twitter and Instagram, but also WhatsApp and LinkedIn. The participants are asked to predict how many hours they will spend on social media during the next seven days (starting tomorrow), and afterwards they will be asked what their personal ideal time spent on social media during (the next) seven days would be. In order to make a proper prediction, they receive a short explanation of how to find the amount of time spent on social media during a certain time period on their phone.

A random part of participants will now receive a question about a commitment device for their social media use. This consistent of an application with which you can lock either your entire phone (you will still be able to make calls, for example in case of emergency) or a particular application for a self-determined time. During this time, you are unable to receive notifications on your phone or from this particular app and you are unable to open the app itself. After the set time is over, your phone will go back to normal. The participants will be asked on a scale of one to ten how attractive such an application sounds to them, and how likely they are to use it themselves. Finally, all participants will then be informed that they will be receiving a second, short survey in seven days, and they will be asked to fill in their email address in order to receive this second survey.

Seven days after finishing the first survey, the participants receive the second survey via e-mail, in which they must enter the actual hours they spent on social media during the recorded seven days. They are once again informed of the used definition of social media and explained where to find the amount of time they spent. They will also be asked whether they think their actual time corresponds to their original prediction. In order to keep their responses anonymous, but to still be able to connect the first and second survey, each participant will receive a unique code in the invitation e-mail to fill in at the start of the second survey. If they did not finish the survey within 48 hours, they will receive a reminder, and they received multiple reminders during the days after that if the survey was not yet finished. Unfortunately, not all participants finished the second part of the survey after these reminders. This could be due to them forgetting, not wanting to do the second part or not receiving the e-mail or not reading the e-mail because it arrived in their spam.

The results from this survey will be analysed using various methods. First, all participants will be categorized as time-consistent and time-inconsistent, but there will be a third category of reverse time-inconsistent participants (Sayman & Öncüler, 2009). This group consists of participants who actually spent less time on social media than their planned ideal. These participants could also be called overachievers (Cobb-Clark et al., 2021), since they achieved an even stronger result than ideally planned.

In order to test whether a participant is time-consistent, the actual time will be compared to the ideal time. A person would be marked as time-inconsistent if these differed thirty minutes or more. This is done to control for small unpredictable shocks. Spending a few minutes more on social media over the span of a week would not be a big deal. Then, to test whether a participant is time-inconsistent or reverse time-inconsistent, the sign of the difference will be analysed. If the difference is negative, this means that the participant is reverse time-inconsistent. A dummy variable will be created, which takes on the value of one if the participant is time-inconsistent, and a value of zero otherwise. A second dummy-variable will be created, taking on the value of one if the participants is reverse time-inconsistent, and a value of zero otherwise. After the first analysis, only normal time-inconsistent participants are used. As we are interested in self-control problems, the reverse time-inconsistent participants are no longer of use, since they do not have the self-control problem of spending too much time on social media.

Now, all time-inconsistent participants are categorised into either naïve, partial-naïve and sophisticate. This is done by measuring the difference between the predicted time and ideal time. We will call this the predicted difference. If the predicted difference is equal to zero, the participant is marked as naïve, as they did not predict any time-inconsistency for themselves while turning out to be time-inconsistent. This means they were completely unaware of their own time-inconsistency. If this difference is 30 minutes or more, the participant can either be partial-naïve or sophisticated. In order to calculate this, the difference between predicted time and actual time is calculated. We call this the unpredicted difference. If this difference is smaller than 30 minutes, the participants is marked as sophisticated, as they were fully able to predict their own time-inconsistency. We once again use the 30 minutes as a mean to control for small shocks. Since most people spent quite a lot of hours on social media during a week, predicting their time of use no further than 30 minutes is already very close. This measure purposefully was not used when determining the naïve participants, as predicting a very small difference would already show some sophistication. The remaining participants are marked as partial-naïve, as they were able to predict that they would be time-inconsistent, but could not properly predicted the size of the inconsistency. Two dummy variables will be created, with the dummy variable for sophistication taking on the value of one if the participant is sophisticated, and the value of zero otherwise, and the dummy variable for partial-naiveté taking on the value of one if the participant is partial-naïve, and zero otherwise.

Next, a new variable will be created that serves as a continuous sophistication level. Here, we specify partial-naïveté as the part of the gap between actual time and ideal time that the participant is able to properly predict. This was done in a similar way by Cobb-Clark et al. (2021) in their research on predicted weight-loss. The calculation of the sophistication level of a random participant is as follows:

$$\text{Sophistication level} = \frac{\text{Predicted time} - \text{Ideal time}}{\text{Actual time} - \text{Ideal time}}$$

Using this calculation, we can measure how strong a participants sophistication is, the scale of their awareness of their time-inconsistency and their ability to predict the time. Each participant received a sophistication level between zero and one. Naïve participants automatically have a sophistication level of zero, as predicted time and ideal time are equal, and fully sophisticated participants automatically have a sophistication level of one, as predicted time and actual time are equal, so this mostly tells us something about partial-naïve participants. As we have marked any participant that had less than 30 minutes between their predicted time and actual time as fully sophisticated, there might be some sophisticated participants with a sophistication level just below or above one.

As another measure of the awareness of time-inconsistency, in the second survey, participants are asked whether they think they made the correct prediction in the first survey or not. We will call this measure the ex-poste prediction recall. It is used to investigate whether or not the participant is able to recall their prediction and properly assess whether it corresponds to their actual time. Learning from experience is very important in sophistication, as is shown by Ali (2011). Being able to remember whether or not you made the right prediction is an important step in learning how to improve self-control and become more sophisticated.

A dummy variable is created that takes on a value of one if the participant answered this question correctly (answering No if their prediction was indeed wrong, or Yes if their prediction was indeed right) and a value of zero if the participants did not answer correctly (answering No while their prediction was correct, or Yes while their prediction was incorrect). This means that the dummy will take a value of one if the participant is able to recall their prediction properly.

In the construction of the survey, the question rose whether to ask participants about their preference for the application in the first survey or in the second survey. The concerns with asking it in the first survey were that some participants, especially sophisticates, might be encouraged to start using such an application during the experiment, thus influencing the actual time they would report in the second survey. However, asking this question in the second survey could influence their answer, as the participant might have gotten an awareness of their time-inconsistency that they did not have at the start of the survey, thus possibly increasing their interest in the application without their current state of awareness being properly reported in the survey. In order to test whether this had an influence an experiment was done in which part of the participants received the question only in the second survey, and part of the participants received it in both the first and the second survey.

These groups will from now on be called the base group and experiment group respectively. We create a dummy variable that takes on the value of zero when a participant is placed in the base group, and a value of one when the participant in placed in the experiment group.

Statistical methods

In the analysis of the above mentioned data, multiple statistical methods will be used. Most importantly, an OLS (Ordinary Least Squares) regression will be used to measure the influence of multiple variables on the attractiveness of the application and the likelihood of use of the application. The following regression is used:

$$Y1_i = \alpha + TI_i\beta 1 + RTI_i\beta 2 + \varepsilon_i \qquad Y2_i = \alpha + TI_i\beta 1 + RTI_i\beta 2 + \varepsilon_i$$

$Y1_i$ is the measure of attractiveness of the application for participant i, and $Y2_i$ is the measure of likelihood of use of the application for participant i. TI is the dummy variable that takes on the value of one when a person is time-inconsistent, and RTI is the dummy variable that takes on the value of one when a person is reverse time-inconsistent. The constant is represented by α, β1 and B2 measure the effect of the variable TI and RTI respectively on $Y1_i$ and $Y2_i$. The error term is represented by ε. The constant can be interpreted as the value of Y when participant i is time-consistent.

For this regression, no control variables will be added. This is because we want to see the difference between being time-consistent and being time-inconsistent or reverse time-inconsistent on attractiveness and likelihood use of the application. This will also be the case for multiple other regressions that will be done using the same basic formula, but with different independent variables: Sophistication category, sophistication level and prediction recall. As a secondary analysis, all of these regressions will also be done using all available control variables: Age, Gender, Education and Country, in order to show the relationship between the independent variable and the attractiveness and likelihood of use of the application, controlling for these factors. All different regression formulas with explanation of all variables can be found in Appendix A.

Then, in order to test the results for the experiment, we must first check if the randomisation was successful. For the randomisation check, we use a Pearson Chi-squared test and a two-sample t-test. The Pearson Chi-squared test is used for the variables Age, Education and Country, as these all have three or more categories. Therefore, comparing means would not make sense. For the variable Gender, there were three options, but only two of them were actually selected by participants. Therefore, it has become a binary variable and the means can be compared via an unpaired two-sample t-test. The Pearson Chi-squared test uses the following formula:

$$\chi^2 = \sum_{i=1}^{r} \sum_{j=1}^{c} \frac{(O_{ij} - E_{ij})^2}{E_{ij}}$$

X^2 is the Pearson Chi-squared test statistic and r and c are the rows (categories of the variable) and c are the columns (base group or experiment group). O_{ij} is the observed frequency for row *i* and column *j*, and E_{ij} is the expected frequency for row *i* and column *j*. The expected frequency depends on the null hypothesis, which in this case is that there is no significant difference between the columns, meaning that there is no significant difference between the base group and the experiment group. The degrees of freedom equal (r-1)(c-1), but since there are only two columns in all tests here, the degrees of freedom automatically equal r-1.

After the randomisation check is completed, a regression will be done of the binary variable of being in the experiment or not on attractiveness of the application, likelihood of use of the application, sophistication level and ex-poste prediction recall. If we do not find any meaningful significant differences, we can conclude that being asked the question in the first and second survey does not change these results compared to only being asked the question in the second survey, and for the purpose of our analysis, we can pool the results of the two groups. Finally, both paired and unpaired two-sample t-tests are used to calculate the means of attractiveness and likelihood of use of the application. First, the unpaired test will be used to compare the means of the responses to attractiveness in the first and second survey and likelihood of use in the first and second survey. Since these groups are the base group and experiment group, they are independent, which is why we use the unpaired t-test. We use the paired t-test to compare the means of attractiveness and likelihood of use in the first survey, and of attractiveness and likelihood of use in the second survey, using only the experiment group. This will be done before all other analyses, so we are sure that the data is useful and not influenced by the experiment.

Results

The first survey received a total of 93 responses. Some of these had to be removed, due to not completing the entire survey, submitting wrong or incoherent information or not submitting a (valid) email address. This left a total of 81 responses, who were all sent the second survey seven days after finishing the first survey. If they did not respond within 48 hours, they would receive a reminder, and if they continued to not respond, they would receive two more reminders afterwards. Unfortunately, there were still some participants who did not respond to the second survey, and because of this, 8 more participants were removed from the study. This left a total of 73 complete responses. The distribution of demographic details of participants can be found in table 1.

Table 1: *Frequency table of demographics*

		Frequency	Percentage
Gender	Male	20	27.40%
	Female	53	72.60%
	Other/Prefer not to say	0	0%
Age	18-24	22	30.14%
	25-34	21	28.77%
	35-51	8	10.96%
	51+	22	30.14%
Education	No schooling completed	0	0%
	High school or equivalent	2	2.74%
	MBO	18	24.66%
	HBO	30	41.09%
	WO Bachelor's Degree	11	15.07%
	WO Master's Degree	12	16.44%
Nationality	The Netherlands	68	93.15%
	Another European Country	3	4.11%
	A country outside of Europe	2	2.74%

Note: Data from Qualtrics survey.

All participants entered their expected, ideal and actual time spent on social media. Comparing these resulted in a total of 6 participants (8.22%) who were time-consistent, 52 participants (71.23%) who were time-inconsistent and 15 participants (20.55%) who were reverse time-inconsistent. In table 2 we find the summary statistics for actual, ideal and predicted time for each category and the full sample.

Table 2: *Summary statistics full sample, time-consistent, time-inconsistent and reverse time-inconsistent participants.*

	Variable	Frequency	**Mean hours**	**Std. Dev.**
Full sample	Predicted time	73	11.16	9.39
	Ideal time	73	6.32	5.20
	Actual time	73	11.25	9.76
Time-consistent	Predicted time	6	8.71	10.57
	Ideal time	6	6.46	6.32
	Actual time	6	6.54	6.26
Time-inconsistent	Predicted time	52	10.27	8.73
	Ideal time	52	5.18	4.18
	Actual time	52	13.17	10.42
Reverse time-	Predicted time	15	15.22	10.59
inconsistent	Ideal time	15	10.20	6.34
	Actual time	15	6.49	5.75

Note: Data from Qualtrics survey, summarized by Stata.

Next, there is the measure of all 52 time-inconsistent participants to see if they are naïve, partial-naïve or sophisticated. Through these calculations, we ended up with 8 naïve participants (15.09%), 15 sophisticated participants (28.30%) and 29 partial-naïve participants (54.71%). It was to be expected the final group of partial-naïve participants would be the largest, as many people seem to be aware of the fact that the time they spent on social media differs from their ideal amount of time on social media, but they might not be aware of the exact amount. The phrasing of the question could also have influenced this. In asking the participants for their predicted time first, after which they are asked their ideal time, they might be inclined to give a different answer to the second question, causing the groups of naïve participants to be smaller. In table 3, we find the summary statistics for actual, ideal and predicted time for each category of sophistication.

Table 3: *Summary statistics sophisticated, partial-naïve and naïve participants.*

	Variable	Frequency	**Mean hours**	**Std. Dev.**
Sophisticated	Predicted time	15	11.62	9.19
	Ideal time	15	5.53	4.09
	Actual time	15	11.63	9.16
Partial-naïve	Predicted time	29	10.56	9.05
	Ideal time	29	4.59	3.49
	Actual time	29	14.08	11.82
Naïve	Predicted time	8	6.69	6.39
	Ideal time	8	6.69	6.39
	Actual time	8	12.76	7.45

Note: Data from Qualtrics survey, summarized by Stata.

To be able to test the results of the experiment (receiving the question in both the first and second survey), we will check whether the randomization was successful. We do this by testing whether the individual characteristics of the participants between the two groups differ significantly from each other. A Pearson Chi-squared test is used for the categorical variables, Nationality, Education and Age, while a t-test is used for the binary variable Gender. We use a null-hypothesis that there is no significant difference between the base group and the experiment group. If we find a p-value below 0.05, we would have to reject this null-hypotheses, meaning that there would be a significant difference between the base group and the experiment group and there would be a problem in the randomization. In table 4, 5 and 6, we see the results from the Pearson Chi-squared test.

Table 4: *Distribution of age in the experiment and base group*

Age	Experiment		Total
	0	1	
18-24	42.86%	57.14%	100%
25-34	47.37%	52.63%	100%
35-51	50.00%	50.00%	100%
51+	52.63%	47.37%	100%
Total	47.76%	52.24%	100%

Note: Data from Qualtrics survey. Pearson chi-squared(3) = 0.4003, Pr = 0.940. 0 means the participant got assigned to the base group, while 1 means that the participant got assigned to the experiment group.

Table 5: *Distribution of nationality in the experiment and base group*

Education	Experiment		Total
	0	1	
High school or equivalent	100%	0.00%	100%
MBO	35.29%	64.71%	100%
HBO	44.44%	55.56%	100%
WO Bachelor’s degree	60.00%	40.00%	100%
WO Master’s degree	54.55%	45.24%	100%
Total	47.76%	52.24%	100%

Note: Data from Qualtrics survey. Pearson chi-squared(4) =4.1689, Pr = 0.384. 0 means the participant got assigned to the base group, while 1 means that the participant got assigned to the experiment group.

Table 6: *Distribution of education in the experiment and base group*

Nationality	Experiment		Total
	0	1	
The Netherlands	48.39%	51.61%	100%
Another European country	33.33%	66.67%	100%
A country outside of Europe	50.00%	50.00%	100%
Total	47.76%	52.24%	100%

Note: Data from Qualtrics survey. Pearson chi-squared(2)= 0.2641, p-value = 0.876. 0 means the participant got assigned to the base group, while 1 means that the participant got assigned to the experiment group.

In the distribution of Age, we see all categories have a very balanced distribution, with the most skewed being 18-24, with 57.14% of participants in this category in the experiment group. The Pearson Chi-squared statistic for age is 0.4003 with three degrees of freedom, with a p-value of 0.940. This is very high above 0.05, meaning we have no statistical evidence to reject the null-hypothesis that there is no significant difference between the base group and the experiment group. We see similar, although slightly more skewed results in the categories for Education and Nationality. Here, from participants with MBO, 64.71% are in the experiment group, and from participants with WO Bachelor's Degree, 60% are in the base group. These distributions are still quite good, but slightly worse than in other categories. Only participants with their highest education being High school or equivalent are not distributed well, as all participants are in the base group. However, this is not very surprising, as there were only two participants in this category. The Pearson Chi-squared statistic for education is 4.1689 with four degrees of freedom, with a p-value of 0.384. We can once again conclude that there is not enough evidence to reject the null-hypothesis that there is no significant difference. Finally, we see another very good distribution among the Nationality categories. The category of Another European Country seems to be skewed, but as there were only three participants in this category, this was the best possible distribution. The Pearson Chi-squared statistic for education is 0.2641 with four degrees of freedom, with a p-value of 0.876. This means that we can once again not reject the null-hypothesis, meaning that randomization was successful for all three of these categories.

Table 7: *Distribution of Gender in the experiment and base group*

	Frequency	Mean	Std. Err.
Base group	32	0.656	0.085
Experiment group	35	0.829	0.065
Total	67	0.746	0.054
Difference		-0.172	0.106

Note: Data from Qualtrics survey. t(65)= -1.6269, p=0.1086. *Male=0 and Female=1*

In table 7, we can find the results from the t-test on the distribution of gender in the base group and experiment group. As none of the participants stated that they belonged to the category Other/Prefer not to say, this becomes a binary variable with 0 representing male and 1 representing female. If we finds a p-value below 0.05, we would have to reject the null-hypothesis that there is no significant difference in the distribution of gender between the base group and the experiment group. As there were more women than men in the sample, we see that the average between the two groups is 0.746. In the base group, this average is 0.656, while in the experiment group the average is 0.829. We find a p-value of 0.1086, meaning that we cannot reject the null-hypothesis, and our randomization was also successful in this category.

Now that we know the randomization of the experiment was successful, we must check whether being in the experiment group itself, so that having been asked the question in the first survey, influences the data collected in this study. In table 8, we see the results from the regression of being in the experiment group or not on Attractiveness of the application, likelihood of use of the application, sophistication level and prediction recall respectively. For this regression, all available control variables are used, with the most represented category being used as the reference category. If we find any significant results, this would mean that being in the experiment group, having been asked the question in the first and second survey, would influence the results compared to only having been asked the question in the second survey. Luckily, we do not find any significant results from the being in the experiment group, so we can conclude that the experiment did not have an influence on the responses to the other questions. The p-values are 0.257, 0.975, 0.655 and 0.915 respectively, all being high above 0.05.

Table 8: *Effect of experiment on Attractiveness and likelihood of use of application, sophistication level and prediction recall.*

		Attractiveness	Likelihood of use	Soph. level	Prediction recall
	Experiment group	-0.812	0.023	-0.058	0.013
		(0.709)	(0.754)	(0.130)	(0.123)
Age	25-34	-1.177	-1.079	-0.381**	-0.153
		(0.959)	(1.020)	(0.181)	(0.166)
	35-51	0.832	1.112	-0.079	-0.153
		(1.241)	(1.321)	(0.212)	(0.215)
	51+	-2.205**	-1.672	-0.337*	-0.058
		(0.968)	(1.030)	(0.194)	(0.168)
Education	High school or	-0.030	0.478	0.495	-0.244
	equivalent	(2.170)	(2.309)	(0.423)	(0.377)
	MBO	0.483	1.121	-0.156	-0.058
		(0.888)	(0.944)	(0.156)	(0.154)
	WO Bachelor's Degree	-0.795	-0.200	-0.412	-0.091
		(1.178)	(1.253)	(0.245)	(0.205)
	WO Master's Degree	1.968*	2.272*	0.487**	0.001
		(1.118)	(1.189)	(0.209)	(0.194)
Gender	Male	-1.216	-1.035	-0.094	-0.009
		(0.916)	(0.974)	(0.181)	(0.159)
Nationality	Another	0.882	0.504	0.187	0.276
	European Country	(1.791)	(1.905)	(0.323)	(0.311)
	A country outside of Europe	-2.616	-1.785	-0.254	-0.228
		(2.089)	(2.222)	(0.446)	(0.363)
Constant		6.735***	5.194***	0.842***	0.801***
		(0.947)	(1.01)	(0.171)	(0.164)
R^2		0.219	0.179	0.322	0.050
Observations		73	73	43	73

Note: Data from Qualtrics survey. OLS regressions with standard errors in parentheses. Significance levels: ***p<0.01, **p<0.05, *p<0.10

Table 9: *Two-sample t-test on Attractiveness_1 and Attractiveness_2*

	Frequency	Mean	Std. Err.
Attractiveness_1	35	5.743	0.398
Attractiveness_2	35	5.514	0.440
Difference		0.229	0.594

Note: Data from Qualtrics survey. t(34)= 0.3850, p=0.7014

Table 10*: Two-sample t-test on Use_1 and Use_2*

	Frequency	Mean	Std. Err.
Use_1	35	4.771	0.420
Use_2	35	5.314	0.486
Difference		-0.543	0.363

Note: Data from Qualtrics survey. t(34)= -1.4960, p=0.1439

In table 9 and 10, we see the results from the two-sample t-test on the difference in mean between the attractiveness and likelihood of use of the application reported by the experiment group in the first survey (Attractiveness_1 and Use_1) and the second survey (Attractiveness_2 and Use_2). In both cases, we find differences that are not too large and large enough p-values, meaning that there is no significant difference in attractiveness and likelihood of use of the application reported in the first and second survey. The expectation was that being made aware of time-inconsistency would increase the answer given in the second survey. However, the awareness they received might have been overestimated. There were many time-inconsistent participants who thought they spent the same amount of time as predicted (as reported by the ex-poste prediction recall), while this was not the case. Thus, the survey itself was probably not strong enough to increase their awareness. The above results give us enough evidence that being asked the question in the first and second survey versus being asked the question in only the second survey did not matter for the eventual results. Therefore, we can pool our data and use it to study the influence of time-inconsistency and sophistication on the attractiveness and likelihood of the application. In table 11 , we can see the results of the OLS regression done on the influence of time-inconsistency on the attractiveness and likelihood of use of the application.

Table 11: *Effect of being time-inconsistent or reverse time-inconsistent on the attractiveness and likelihood of use of the application*

	Attractiveness	Likelihood of use
Time-inconsistent	2.776**	3.167**
	(1.228)	(1.243)
Reverse time-inconsistent	0.967	1.200
	(1.356)	(1.393)
Constant	3.167***	2.333*
	(1.146)	(1.17)
R^2	0.111	0.129
Observations	73	73

Note: Data from Qualtrics survey. OLS regressions, with standard errors in parentheses. Significance levels: ***p<0.01, **p<0.05, *p<0.10

The results of these regressions can be interpreted as the change in the attractiveness of the application and the likelihood of use of the application when being (reverse) time-inconsistent instead of time-consistent. For a time-inconsistent person, the attractiveness and likelihood of use of the application are suggested to increase with 2.776 and 3.167 respectively in comparison to a time-consistent person, with p-values 0.025 and 0.013. This suggests that he reported value of attractiveness and likelihood of use of the application is higher when a person is time-inconsistent compared to them being time-consistent. The results for reverse time-inconsistent participants is lower and insignificant, with p-values 0.478 and 0.392 respectively. It seems that being reverse time-inconsistent does not have a significant influence on the attractiveness and likelihood of use of the application compared to being time-consistent. We can take away from these results that in this sample, time-consistent participants on average found the proposed application less attractive and they were less likely to use the application themselves than time-inconsistent participants, showing that the direction of the attractiveness and likelihood is positive when looking at time-inconsistency compared to time-consistency. We are mainly interested in this, the difference irrespective of what underlying factors drive being time-consistent or (reverse) time-inconsitent. In order to improve the coefficient as much as possible, we will also be doing a regression using all available control variables. These results can be found in table 12.

Table 12: *Effect of being time-inconsistent or reverse time-inconsistent on the attractiveness and likelihood of use of the application, controlling for age, education, gender and nationality*

		Attractiveness	Likelihood of use
	Time-inconsistency	1.920	2.376*
		(1.255)	(1.311)
	Reverse time-inconsistency	0.629	0.955
		(1.384)	(1.446)
Age	25-34	-1.048	-0.909
		(0.950)	(0.992)
	35-51	0.619	0.744
		(1.235)	(1.290)
	51+	-1.995**	-1.395
		(0.965)	(1.008)
Education	High school or equivalent	0.491	0.402
		(2.103)	(2.196)
	MBO	0.182	0.836
		(0.893)	(0.933)
	WO Bachelor’s Degree	-0.673	-0.201
		(1.155)	(1.207)
	WO Master’s Degree	1.817	2.005*
		(1.109)	(1.159)
Gender	Male	-0.874	-0.838
		(0.903)	(0.943)
Nationality	Another European Country	0.047	-0.167
		(1.781)	(1.860)
	A country outside of Europe	-2.451	-1.612
		(2.077)	(2.169)
Constant		4.729***	3.317**
		(1.439)	(1.503)
R^2		0.250	0.240
Observations		73	73

Note: Data from Qualtrics survey. OLS regressions with standard errors in parentheses. Significance levels: ***p<0.01, **p<0.05, *p<0.10

Here we find similar results to the original regression without control variables, although with smaller and less significant coefficients, with the attractiveness and likelihood of use having a coefficient of 1.920 and 2.376 respectively for time-inconsistency, with p-values 0.131 and 0.075. This suggests that some of the variation found previously is explained by our control variables, as both coefficients went down by around 0.8, but that still suggesting that there is a positive difference between time-inconsistent and time-consistent participants in the attractiveness and likelihood of use of the application. The coefficients for reverse time-inconsistency are lower and more insignificant, at p-values 0.651 and 0.511 respectively, still suggesting that this has no significant influence on attractiveness and likelihood of use of the application.

From now on, we will be focusing mainly on the group of 52 time-inconsistent participants. As before, we will do an OLS regression on the attractiveness and likelihood of use of the application when belonging to a certain category of time-inconsistent participants. We use the dummy variables for sophistication and partial-naiveté for this. This way, we can compare the effect of being fully sophisticated or partial-naïve versus being fully naïve. The results are found in table 13.

Table 13: *Effect of being in a certain sophistication category on attractiveness and likelihood of use of application*

	Attractiveness	Likelihood of use
Sophisticated	5.025***	5.258***
	(1.032)	(1.135)
Partial-naive	3.797***	3.780***
	(0.951)	(1.035)
Constant	2.375***	1.875**
	(0.842)	(0.916)
R^2	0.328	0.307
Observations	52	52

Note: Data from Qualtrics survey. OLS regressions, with standard errors in parentheses. Significance levels: ***p<0.01, **p<0.05, *p<0.10

The results strongly suggest that becoming more aware of your time-inconsistency also increases the attractiveness and likelihood of use of the application. For the attractiveness of the application, being partial naïve as compared to being naïve has a coefficient of 3.797, and being sophisticated had an even bigger coefficient at 5.025, both significant at p-value 0.000. The same goes for likelihood of use of the application, with coefficients being 3.780 and 5.258 for partial-naïve and sophisticated, with p-values 0.000 and 0.001 respectively. This provides some very strong evidence to believe that being partial-naïve instead of naïve makes the application more attractive and makes one more likely to use it, and that being sophisticated instead of naïve makes it even more attractive and makes one even more likely to use it.

However, there is still the issue that there exists a lot of variation within the group of partial-naïve participants that is not captured by putting all partial-naïve participants in one group. In order to have a more balanced result, we use the continuous sophistication level that we calculated.

Within our time-inconsistent participants, we find some that some have an actual time that is lower than their predicted time, but higher than their ideal time. Because of this, they were not classified as reverse time-inconsistent. However, Cobb-Clark et al. (2021) name these participants as overachievers as well, as they achieve a stronger results than they predicted. This overachieving causes them to have a very high (above 1) sophistication level. These levels would have a very strong influence on the results if taken into the calculation. Similar to Cobb-Clark et al. (2021), these participants will be removed from the sample for this specific analysis, removing a total of 9 participants (17.31%) from our sample of 52 time-inconsistent participants. This was, we calculate the effect only using measurements between 0 and 1 (or in one case, a sophisticate measured just slightly above 1), leaving us with a total of 43 participants. This leaves us with a smaller sample than preferred, but it will still be enough to calculate a reliable result of the effect of sophistication level on the attractiveness and likelihood of use of the application. In table 14, we find the results from this OLS regression:

Table 14: *Effect of sophistication level on attractiveness and likelihood of use of application*

	Attractiveness	Likelihood of use
Sophistication level	3.318***	3.440***
	(1.017)	(1.060)
Constant	4.109***	3.784***
	(0.705)	(0.735)
R^2	0.206	0.205
Observations	43	43

Note: Data from Qualtrics survey. OLS regressions, with standard errors in parentheses. Significance levels: ***p<0.01, **p<0.05, *p<0.10

Both of these regressions once again give us an extremely significant positive result. This suggests that an increase in your sophistication level results in an increase in both the attractiveness and the likelihood of using the application. These results imply that your sophistication level going up from 0 to 1 means an increase of 3.318 and 3.440 respectively, both significant at p-value 0.002. However, going from naïve to fully sophisticated is unlikely. Therefore, we can also interpret these results as an increase of 0.03318 in the attractiveness of the application and an increase of 0.0344 in the likelihood of use of the application when there is an increase of 0.01 in your sophistication level, which gives us a clearer idea of the actual effect. This is very strong evidence for the fact that awareness of time-inconsistency indeed influences both the attractiveness of a commitment device and the likelihood of use of the commitment device with regards to social media use in a positive way.

In table 15 and 16, we find the above regressions done once again with all available control variables. We are mainly interested in the difference in reported attractiveness and likelihood of the application reported by participants with different sophistication categories and sophistication levels, irrespective of wat underlying factors drive sophistication. Our results strongly suggest that this difference is positive for participants with higher sophistication levels or in sophistication categories that are further from naïve. We will now calculate these coefficients again, where we control for all available control variables, as it is also interesting to see if sophistication is still associated with attractiveness and likelihood of use, even after controlling for these variables. We slightly higher, but very similar and still highly significant results, with the coefficients being 5.456 and 5.690, and 3.760 and 3.954 respectively, with all p-values being between 0.000 and 0.003.

Table 15: *Effect of being in a certain sophistication category on the attractiveness and likelihood of use of the application, controlling for age, education, gender and nationality*

		Attractiveness	Likelihood of use
	Sophisticated	5.456***	5.690***
		(1.026)	(1.154)
	Partial-naïve	4.032***	4.064***
		(0.986)	(1.110)
Age	25-34	0.221	0.251
		(0.890)	(1.001)
	35-51	1.305	1.259
		(1.049)	(1.180)
	51+	0.120	0.234
		(0.945)	(1.064)
Education	High school or	-5.639**	-4.948*
	equivalent	(2.373)	(2.670)
	MBO	0.526	1.345
		(0.772)	(0.868)
	WO Bachelor's Degree	0.319	0.662
		(1.108)	(1.246)
	WO Master's Degree	0.384	0.884
		(1.110)	(1.249)
Gender	Male	-0.938	-0.539
		(0.934)	(1.051)
Nationality	Another	-1.197	-1.457
	European Country	(1.469)	(1.653)
	A country outside of Europe	-4.763*	-4.685*
		(2.420)	(2.723)
Constant		2.063*	1.025
		(1.144)	(1.287)
R^2		0.548	0.503
Observations		52	52

Note: Data from Qualtrics survey. OLS regressions with standard errors in parentheses. Significance levels: ***p<0.01, **p<0.05, *p<0.10

Table 16: *Effect of sophistication level on the attractiveness and likelihood of use of the application, controlling for age, education, gender and nationality*

		Attractiveness	Likelihood of use
	Sophistication level	3.760***	3.954***
		(1.178)	(1.198)
Age	25-34	-0.263	-0.488
		(1.271)	(1.293)
	35-51	0.456	0.038
		(1.398)	(1.422)
	51+	0.133	0.209
		(1.336)	(1.359)
Education	High school or	-5.650*	-5.028*
	equivalent	(2.816)	(2.864)
	MBO	1.057	2.071*
		(1.032)	(1.049)
	WO Bachelor's Degree	1.451	1.558
		(1.665)	(1.693)
	WO Master's Degree	0.861	1.340
		(1.483)	(1.508)
Gender	Male	-0.903	1.642
		(1.200)	(1.220)
Nationality	Another	-2.143	-3.513
	European Country	(2.138)	(2.174)
	A country outside of Europe	-4.708	-5.254*
		(2.897)	2.946)
Constant		3.757**	2.866*
		(1.442)	(1.466)
R^2		0.449	0.475
Observations		43	43

Note: Data from Qualtrics survey. OLS regressions with standard errors in parentheses. Significance levels: ***p<0.01, **p<0.05, *p<0.10

Finally, the participants are asked whether or not they think they made the correct prediction in the first survey. This is the ex-poste prediction recall, being able to remember your prediction and connect it to your actual time. In total, 22 participants (30.14%) answered this question incorrectly, and 51 participants (69.86%) answered it correctly. In table 17, we find the results of the OLS regression on the effect of correctly recalling your prediction on the attractiveness and likelihood of use of the application. For this regression, the entire sample is used. In table 18, we find a second regression using only the group of time-inconsistent participants.

Table 17: *Effect correctly recalling your prediction on attractiveness and likelihood of use of application*

	Attractiveness	Likelihood of use
Correct prediction recall	1.336*	1.782**
	(0.737)	(0.753)
Constant	4.409***	3.591***
	(0.616)	(0.630)
R^2	0.044	0.073
Observations	73	73

Note: Data from Qualtrics survey. OLS regressions, with standard errors in parentheses. Significance levels: ***p<0.01, **p<0.05, *p<0.10

Table 18: *Effect correctly recalling your prediction on attractiveness and likelihood of use of application*

	Attractiveness	Likelihood of use
Correct prediction recall	2.077**	2.821***
	(0.872)	(0.903)
Constant	4.385***	3.385***
	(0.755)	(0.782)
R^2	0.102	0.147
Observations	52	52

Note: Data from Qualtrics survey. OLS regressions, with standard errors in parentheses. Significance levels: ***p<0.01, **p<0.05, *p<0.10

In both regressions, we see that there is a significant difference between the group that recalled their prediction correctly, and the group that did not, irrespective of what underlying factors drive the ability to properly recall your prediction. The results suggest that participants that are able to recall their prediction correctly, also report a higher attractiveness and likelihood of use of the application. In the regression using only the time-inconsistent participants, the coefficients are around a point higher. This makes sense, as time-consistent participants are often able to recall their prediction, but as previously seen, they report a lower attractiveness and likelihood of use of the application than time-inconsistent participants. We also remove the reverse time-inconsistent participants as both the time-consistent and reverse time-inconsistent participants are not too interesting for this measure, since Only doing this regression with the time-inconsistent participants gives us a more interesting and useful result. The results suggest that being able to properly recall your prediction increases the reported attractiveness and likelihood of use of the application. As said before, learning is an important part in developing sophistication. Being able to know whether you made a correct prediction is part of this learning process, and it implies that a participant would find a soft commitment device more attractive and would be more likely to use it if they are already in a further stage of learning about their time-inconsistency.

In table 19, we find the regression using the group of time-inconsistent participants done again using all available control variables. Previously, this was not done, as we are mainly interested in the difference between the participants that correctly recalled their prediction and those who did not. Seeing that the results suggest a positive effect of being able to recall the prediction, we try to make our coefficient as reliable as possible using the available control variables. We find that the coefficients are even stronger and more significant in this case, giving us even stronger evidence that being able to properly recall your prediction increases the attractiveness and likelihood of use of the application for a participant.

Table 19: *Effect of correctly recalling your prediction on attractiveness and likelihood of use of application controlling for age, education, gender and nationality*

		Attractiveness	Likelihood of use
	Correct prediction recall	2.661***	3.530***
		(0.846)	(0.865)
Age	25-34	-0.275	-0.201
		(1.015)	(1.038)
	35-51	1.632	1.813
		(1.192)	(1.219)
	51+	-0.156	0.073
		(1.082)	(1.106)
Education	High school or equivalent	-4.325	-3.695
		(2.705)	(2.765)
	MBO	0.665	1.564*
		(0.903)	(0.923)
	WO Bachelor's Degree	0.615	1.076
		(1.292)	(1.319)
	WO Master's Degree	2.099	2.708**
		(1.252)	(1.280)
Gender	Male	-1.582	-1.149
		(1.020)	(1.042)
Nationality	Another European Country	-0.784	-1.265
		(1.704)	(1.741)
	A country outside of Europe	-5.723**	-5.980**
		(2.803)	(2.865)
Constant		3.821***	2.093*
		(1.145)	(1.170)
R^2		0.370	0.428
Observations		52	52

Note: Data from Qualtrics survey. OLS regressions with standard errors in parentheses. Significance levels: ***p<0.01, **p<0.05, *p<0.10

Throughout the analysis, we have seen that there are different results for the attractiveness of the application and the likelihood of use of the application. As a final analysis, we can test whether there is a significant difference between the means of Attractiveness and Likelihood of use. We use a two-sample t-test for this, like the one used to check the means for attractiveness and likelihood of use of the application in the first and second survey after the experiment. We find the results in table 20 and 21.

Table 20: *Paired t-test on Attractiveness_1 and Use_1*

	Frequency	Mean	Std. Err.
Attractiveness_1	35	5.742	0.398
Use_1	35	4.771	0.420
Difference		0.971	0.199

Note: Data from Qualtrics survey. t(34)= 4.8895, p=0.0000

Table 21*: Paired t-test on Attractiveness_2 and Use_2*

	Frequency	Mean	Std. Err.
Attractiveness_2	67	5.537	0.351
Use_2	67	5.060	0.373
Difference		0.478	0.123

Note: Data from Qualtrics survey. t(66)= 3.8884, p=0.0002

In table 20 and 21 we see some very interesting results. When comparing the responses to the attractiveness and the likelihood of use of the application, there seems to be a significant difference, reporting p-values of 0.0000 and 0.0002. When looking at the responses given by the experiment group in the first survey, we see almost a full point difference between the means, and when looking at the responses in the second survey, we see almost half a point difference, with attractiveness of the application being higher in both cases. This could possibly be explained by the fact that the attractiveness of the application is a more objective measure than the likelihood of use. Participants who were not interested in using the application themselves could possibly rate the attractiveness higher, as they could consider the application to be objectively attractive, but rate the likelihood of use lower because they are not likely to use the application themselves.

Conclusion and discussion

In this study, we have taken a look at time-inconsistency, especially whether or not people are aware of their own inconsistency when using social media. Before this study, a lot of research was already done regarding time-inconsistency, which often showed that a large portion of people behave inconsistent and that they often are not aware of it. This often has to do with problems surrounding self-control.

This study specifically aimed to research time-inconsistency in the use of social media and the demand for soft commitment devices that could help with self-control problems. We found that less than 10% of the sample was indeed time-consistent, showing that most people are indeed time-inconsistent in their social media use. Around 28% of time-inconsistent participants were sophisticated, meaning that almost three quarters of the participants were not (fully) aware of this time-inconsistency. This is in line with the first hypothesis, namely that a considerable portion of people are time-inconsistent. It also suggests that a large part of them does not realise this properly. These participants, naïfs and partial-naïfs, are unable to predict exactly how much time they will be spending on social media and how much they deviate from their ideal amount of time. This shows self-control problems, which could lead to problematic behaviour.

A commitment device could help with this behaviour. A soft commitment device in the form of an application was suggested to the participants, to which they gave a rating from 1 to 10 on its attractiveness and the likelihood that they themselves would use it. This was connected to their sophistication level, a variable that was created to calculate the awareness of the severity of their self-control problem, looking at the gap between predicted time and actual time that they were unable to predict. The results that were found clearly suggest that participants who are more aware of their time-inconsistency would rate this sort of application higher, both on attractiveness and likelihood of use, than participants who were not or less aware of their time-inconsistency. Participants were also asked whether or not they thought that their actual time spent was the same as the amount of time they predicted in the first survey. Being able to recall their prediction properly, which is a sign that the participant is more aware of their time-inconsistency and is learning about it, was suggested to have a significant positive effect on the reported attractiveness and likelihood of use. All of these results are in line with the second hypothesis, suggesting that awareness of time-inconsistency indeed causes an increase in the attractiveness of the suggested application, and a higher likelihood that they would use such an application.

In regards to the soft commitment device, participants were asked to report the attractiveness and the likelihood that they would use it. One would not immediately expect a difference between these values, as the questions are very similar. However, the results of the final analysis suggest that there is a difference between the reported attractiveness and the reported likelihood of use of the application, with the average likelihood of use reported being lower. This information could be used for the development and marketing of such a soft commitment device, focussing more on what people can get out of it personally instead of more the objective attractiveness.

The most important signal that this study has given, is that awareness of time-inconsistency can be very important in dealing with self-control problems. In this study, we have not been able to confirm whether making people aware of their time-inconsistency would have short-term effects. It was expected that people would become more aware of their time-inconsistency, simply by doing the survey and realising the difference between their actual and predicted time. However, this did not seem to happen, as there was no significant difference between the reported attractiveness and likelihood of use of the application in the first and in the second survey.

Finding a good method to make people aware of their time-inconsistency would be a good next step in time-inconsistency research, and it could also be implemented practically. We have clear evidence that people are time-inconsistent, we have seen that commitment devices often have very positive effects, and we have now seen that being aware of time-inconsistency could increase the attractiveness and likelihood of use of soft commitment devices, increasing the demand for them. If a proper way to give people awareness could be created, preferably on both short-term and long-term, this could have a positive impact on the amount of people that use soft commitment devices, which could then positively impact the behaviour of those people, hopefully helping them better their self-control problems. Combining all knowledge that was collected and bringing it into practice could make a real difference in helping people improve and become more consistent in their choices and action.

This study does have some clear limitations. There could always be unexpected and unpredictable circumstances that cause a participant to use their phone more or less during a certain period of time. For example, during the period in which the participants were tracking their social media use, Ascension day and Pentecost happened. These are both national holidays in the Netherlands, so most people would have been free that day. This could have influenced their social media use, both positively and negatively. In the results, we have controlled for small shocks under 30 minutes when categorizing the participants, but this might not have been enough. Future research could be done over a longer period of time, and finding a way to incorporate a measure for unexpected shocks could increase the accuracy of the results.

The eventual sample size was also smaller than originally hoped. This was partly caused by participants who did not finish the second survey. However, the largest issue was that there were far more overachievers, meaning participants who spent less time on social media than predicted, than expected. Since these participants could not be taken into account during the main analysis, namely that of the sophistication level, the sample size was heavily reduced. For future research, a larger sample size would be good to ensure the validity of the study. Right now, even though we have found significant results and there was an alright balance in most characteristics within the sample, the external validity could be made better by doing to same study with a larger and more diverse group of participants, and over different time periods. This way, more reliable results and more information could be gathered regarding this issue, strengthening our knowledge on time-inconsistency and soft commitment devices.

Overall, this study has shown some very promising results regarding the relationship between awareness of time-inconsistency and the use of soft commitment devices. This knowledge can be used to further research this issue, and it can be used as a way to help people manage and improve on their self-control issues. To take final look at the initial research questions, it seems that both questions can be answered positively. It appears that a considerable portion of people is indeed time-inconsistent, but in many cases not (fully) aware of it. The people who are aware of it, appear to find soft commitment devices more attractive and they are more likely to use them than people who are less aware, showing a significant positive relationship between awareness of time-inconsistency and the demand for soft-commitment devices.

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Appendix A: Regression Formulas

Regressions without control variables

- $Y1_i = \alpha + TI_i\beta 0 + RTI_i\beta 1 + \varepsilon_i \qquad Y2_i = \alpha + I_i\beta 0 + RTI_i\beta 1 + \varepsilon_i$

  Y1i is the measure of attractiveness of the application for participant i, and Y2i is the measure of likelihood of use of the application for participant i. TI is the dummy variable that takes on the value of one when a person is time-inconsistent, and RTI is the dummy variable that takes on the value of one when a person is reverse time-inconsistent. β0 and β1 measure the effect of the variable TI and RTI respectively on Y1i and Y2i. The error term is represented by ε. The constant can be interpreted as the value of Y when participant i is time-consistent. The results can be found in table 11.

- $Y1_i = \alpha + SO_i\beta 0 + PN_i\beta 1 + \varepsilon_i \qquad Y2_i = \alpha + SO_i\beta 0 + PN_i\beta 1 + \varepsilon_i$

  $Y1_i$ is the measure of attractiveness of the application, and $Y2_i$ is the measure of likelihood of use of the application. SO_i is the dummy variable that takes on the value of one when a person is sophisticated, and PN is the dummy variable that takes on the value of one when a person is partial-naïve. β0 and β1 measure the effect of the variable SO and PN on $Y1_i$ and $Y2_i$ respectively. The error term is represented by ε. The constant can be interpreted as the value of Y when participant i is naïve. The results can be found in table 13.

- $Y1_i = \alpha + SL_i\beta 1 + \varepsilon_i \qquad Y2_i = \alpha + SL_i\beta 1 + \varepsilon_i$

  $Y1_i$ is the measure of attractiveness of the application, and $Y2_i$ is the measure of likelihood of use of the application. SL_i represents the sophistication level of the participant. β1 measures the effect of the variable SL on $Y1_i$ and $Y2_i$. The error term is represented by ε. The constant can be interpreted as the value of Y when participant i has a sophistication level equal to zero. The results can be found in table 14.

- $Y1_i = \alpha + PR_i\beta1 + \varepsilon_i \qquad Y2_i = \alpha + PR_i\beta1 + \varepsilon_i$

  $Y1_i$ is the measure of attractiveness of the application, and $Y2_i$ is the measure of likelihood of use of the application. PR_i is the dummy variable that takes on the value of one if participant i is able to properly recall the prediction. β1 measures the effect of the variable PR on $Y1_i$ and $Y2_i$. The error term is represented by ε. The constant can be interpreted as the value of Y when participant i was unable to properly recall their prediction, so the value of the dummy is zero. The results can be found in table 17 and 18.

Regressions with control variables

Interpretation of control variables can be found at the end of Appendix A

- $Y1_i = \alpha + EG_i\beta1 + Age3_i\beta2 + Age4_i\beta3 + Age5_i\beta4 + Edu2_i\beta5 + Edu3_i\beta6 + Edu5_i\beta7 + Edu6_i\beta8 + Gen_i\beta9 + Cou2_i\beta10 + Cou3_i\beta11 + \varepsilon_i$
- $Y2_i = \alpha + EG_i\beta1 + Age3_i\beta2 + Age4_i\beta3 + Age5_i\beta4 + Edu2_i\beta5 + Edu3_i\beta6 + Edu5_i\beta7 + Edu6_i\beta8 + Gen_i\beta9 + Cou2_i\beta10 + Cou3_i\beta11 + \varepsilon_i$
- $Y3_i = \alpha + EG_i\beta1 + Age3_i\beta2 + Age4_i\beta3 + Age5_i\beta4 + Edu2_i\beta5 + Edu3_i\beta6 + Edu5_i\beta7 + Edu6_i\beta8 + Gen_i\beta9 + Cou2_i\beta10 + Cou3_i\beta11 + \varepsilon_i$
- $Y_i = \alpha + EG_i\beta1 + Age3_i\beta2 + Age4_i\beta3 + Age5_i\beta4 + Edu2_i\beta5 + Edu3_i\beta6 + Edu5_i\beta7 + Edu6_i\beta8 + Gen_i\beta9 + Cou2_i\beta10 + Cou3_i\beta11 + \varepsilon_i$

Y1i is the measure of attractiveness of the application for participant i,, Y2i is the measure of likelihood of use of the application for participant I, Y3i is the measure of the sophistication level for participant i and Y4i is the prediction recall of participant i. EG is the dummy variable that takes on the value of one when a person is in the experiment group. β1 measures the effect of EG on Y. The error term is represented by ε. The constant can be interpreted as the value of Y when the participant is in the base group, belongs to age category 2, education category 4, country category 1 and is female. The results can be found in table 8.

- $Y1_i \ = \ \alpha + TI_i\beta 0 + RTI_i\beta 1 + Age3_i\beta 2 + Age4_i\beta 3 + Age5_i\beta 4 + Edu2_i\beta 5 + Edu3_i\beta 6 + Edu5_i\beta 7 + Edu6_i\beta 8 + Gen_i\beta 9 + Cou2_i\beta 10 + Cou3_i\beta 11 + \varepsilon_i$
- $Y2_i \ = \ \alpha + I_i\beta 0 + RTI_i\beta 1 + Age3_i\beta 2 + Age4_i\beta 3 + Age5_i\beta 4 + Edu2_i\beta 5 + Edu3_i\beta 6 + Edu5_i\beta 7 + Edu6_i\beta 8 + Gen_i\beta 9 + Cou2_i\beta 10 + Cou3_i\beta 1\varepsilon_i$

Y1i is the measure of attractiveness of the application for participant i, and Y2i is the measure of likelihood of use of the application for participant i. TI is the dummy variable that takes on the value of one when a person is time-inconsistent, and RTI is the dummy variable that takes on the value of one when a person is reverse time-inconsistent. The constant is represented by α, β0 and β1 measure the effect of the variable TI and RTI respectively on Y1i and Y2i. The error term is represented by ε. The constant can be interpreted as the value of Y when participant i is time-consistent, belongs to age category 2, education category 4, country category 1 and is female. The results can be found in table 12

- $Y1_i \ = \ \alpha + SO_i\beta 0 + PN_i\beta 1 + Age3_i\beta 2 + Age4_i\beta 3 + Age5_i\beta 4 + Edu2_i\beta 5 + Edu3_i\beta 6 + Edu5_i\beta 7 + Edu6_i\beta 8 + Gen_i\beta 9 + Cou2_i\beta 10 + Cou3_i\beta 11 + \ \varepsilon_i$
- $Y2_i \ = \ \alpha + SO_i\beta 0 + PN_i\beta 1 + Age3_i\beta 2 + Age4_i\beta 3 + Age5_i\beta 4 + Edu2_i\beta 5 + Edu3_i\beta 6 + Edu5_i\beta 7 + Edu6_i\beta 8 + Gen_i\beta 9 + Cou2_i\beta 10 + Cou3_i\beta 11 + \varepsilon_i$

$Y1_i$ is the measure of attractiveness of the application, and $Y2_i$ is the measure of likelihood of use of the application. SO_i is the dummy variable that takes on the value of one when a person is sophisticated, and PN is the dummy variable that takes on the value of one when a person is partial-naïve. β0 and β1 measure the effect of the variable SO and PN on $Y1_i$ and $Y2_i$ respectively. The error term is represented by ε. The constant can be interpreted as the value of Y when participant i is naïve, belongs to age category 2, education category 4, country category 1 and is female. The results can be found in table 15

- $Y1_i = \alpha + SL_i\beta 1 + Age3_i\beta 2 + Age4_i\beta 3 + Age5_i\beta 4 + Edu2_i\beta 5 + Edu3_i\beta 6 + Edu5_i\beta 7 + Edu6_i\beta 8 + Gen_i\beta 9 + Cou2_i\beta 10 + Cou3_i\beta 11 + \varepsilon_i$
- $Y2_i = \alpha + SL_i\beta 1 + Age3_i\beta 2 + Age4_i\beta 3 + Age5_i\beta 4 + Edu2_i\beta 5 + Edu3_i\beta 6 + Edu5_i\beta 7 + Edu6_i\beta 8 + Gen_i\beta 9 + Cou2_i\beta 10 + Cou3_i\beta 11 + \varepsilon_i$

$Y1_i$ is the measure of attractiveness of the application, and $Y2_i$ is the measure of likelihood of use of the application. SL_i represents the sophistication level of the participant. β1 measures the effect of the variable SL on $Y1_i$ and $Y2_i$. The error term is represented by ε. The constant can be interpreted as the value of Y when participant i has a sophistication level equal to zero, belongs to age category 2, education category 4, country category 1 and is female. The results can be found in table 16

- $Y1_i = \alpha + PR_i\beta 1 + Age3_i\beta 2 + Age4_i\beta 3 + Age5_i\beta 4 + Edu2_i\beta 5 + Edu3_i\beta 6 + Edu5_i\beta 7 + Edu6_i\beta 8 + Gen_i\beta 9 + Cou2_i\beta 10 + Cou3_i\beta 11 + \varepsilon_i$
- $Y2_i = \alpha + PR_i\beta 1 + Age3_i\beta 2 + Age4_i\beta 3 + Age5_i\beta 4 + Edu2_i\beta 5 + Edu3_i\beta 6 + Edu5_i\beta 7 + Edu6_i\beta 8 + Gen_i\beta 9 + Cou2_i\beta 10 + Cou3_i\beta 11 + \varepsilon_i$

$Y1_i$ is the measure of attractiveness of the application, and $Y2_i$ is the measure of likelihood of use of the application. PR_i is the dummy variable that takes on the value of one if participant i is able to properly recall the prediction. β1 measures the effect of the variable PR on $Y1_i$ and $Y2_i$. The error term is represented by ε. The constant can be interpreted as the value of Y when participant i was unable to properly recall their prediction, so the value of the dummy is zero, belongs to age category 2, education category 4, country category 1 and is female. The results can be found in table 19.

Interpretation of control variables

$Age3_i$ = 1 if participant i belongs to age category 3 (25-35). β2 measures the effect of being in age category 3 as compared to being in age category 2 (18-24).

$Age4_i$ = 1 if participant i belongs to age category 4 (36-50) .β3 measures the effect of being in age category 4 as compared to being in age category 2 (18-24).

$Age5_i$ = 1 if participant i belongs to age category 5 (51+). β4 measures the effect of being in age category 5 as compared to being in age category 2 (18-24).

$Edu2_i$= 1 if participant i belongs to education category 2 (High school or equivalent). β5 measures the effect of being in education category 2 as compared to being in age category 4 (HBO).

$Edu3_i$= 1 if participant i belongs to education category 3 (MBO). β6 measures the effect of being in education category 3 as compared to being in age category 4 (HBO).

$Edu5_i$= 1 if participant i belongs to education category 5 (WO Bachelor's Degree). β7 measures the effect of being in education category 5 as compared to being in age category 4 (HBO).

$Edu6_i$= 1 if participant i belongs to education category 6 (WO Master's Degree). β8 measures the effect of being in education category 6 as compared to being in age category 4 (HBO).

Gen_i= 1 if participant i is male. β9 measures the effect of being male as compared to being female.

$Cou2_i$= 1 if participant i belongs to country category 2 (Another European Country). β10 measures the effect of being in country category 2 as compared to being in age category 1 (The Netherlands).

$Cou3_i$= 1 if participant i belongs to country category 3 (A country outside of Europe). β11 measures the effect of being in country category 3 as compared to being in age category 1 (The Netherlands).

Appendix B - Surveys

Social media

Start of Block: Default Question Block

(For Dutch, see below)

Dear participant,

Thank you for participating in this study on the use of social media. This research is conducted via the Erasmus University for a Bachelor thesis on the use of social media. All your answers are completely confidential and cannot be traced back to you. Participation is voluntary and data collection will be anonymous. The data will be used purely for research purposes and will be deleted four weeks after the completion of the research.

This survey consistent of two parts. Seven days after filling in the first survey, you will be sent the second survey. Both surveys should not take more than around five minutes to complete. There are no right or wrong answers, so please answer to the best of your ability. If you have any questions or concerns about this survey, or you would like to have you answers removed, you can send an e-mail to 434038lk@student.eur.nl or kentin@ese.eur.nl.

Beste deelnemer,

Hartelijk dank voor uw deelname in deze studie over social media gebruik. Deze studie zal worden gedaan via de Erasmus Universiteit Rotterdam. Alle antwoorden worden vertrouwelijk verwerkt. Deelname is vrijwillig en dataverzameling is anoniem. Alle data wordt enkel gebruikt voor onderzoeksdoeleinde en worden vier weken na het voltooien van de studie verwijderd.

Deze enquête bestaat uit twee delen. Zeven dagen na het invullen van deel één van de enquête, wordt het tweede deel van de enquête toegestuurd. Beide enquêtes duren maximaal vijf minuten om in te vullen. Er zijn geen goede of foute antwoorden, antwoord alle vragen zo goed mogelijk. Heeft u vragen over dit onderzoek, of wenst u dat uw antwoorden verwijderd worden, stuur dan een e-mail naar 434038lk@student.eur.nl of kentin@ese.eur.nl.

○ I state that I am voluntarily participating and agree to my responses being anonymously processed for research purposes only. (1)

Page Break

Q1 What is your age? (Wat is uw leeftijd?)

- 17 or younger (1)
- 18-24 (2)
- 25-35 (3)
- 36-50 (4)
- 51 or older (5)

Q2 What is your gender? (Wat is je gender?)

- Male (1)
- Female (2)
- Other / Prefer not to say (3)

Q3 What is your highest level of education (either completed or still enrolled)? (Wat is je hoogst genoten opleiding (afgerond of momenteel volgende))?

- No schooling completed (geen scholing afgerond) (1)
- High school or equivalent (Middelbare school of soortgelijk) (2)
- MBO (3)
- HBO (4)
- WO Bachelor's degree (5)
- WO Master's degree (6)

Q4 Where were you born? (Waar ben je geboren?)

- ◯ The Netherlands (1)
- ◯ Another European country (2)
- ◯ A country outside of Europe (3)

Page Break

This survey is about the time you spend on social media. We define social media as media technology that facilitates the sharing of ideas, thoughts and information through the building of virtual networks and communities. Examples of such media are Facebook, Twitter and Instagram, but also WhatsApp and LinkedIn. To answer the next question, you can go to 'Settings' on your smartphone to view your average or past screentime (depending on your type of phone, it might differ where exactly you can find this).

Deze enquête gaat over de tijd die je aan sociale media besteedt. Onder social media zien we media voor het delen van ideeën, gedachten en informatie doormiddel van het bouwen van online netwerken en communities. Hieronder vallen Facebook, Twitter en Instagram, maar ook media als Whatsapp en LinkedIn. Om de volgende vraag te beantwoorden, kun je naar 'Instellingen' gaan op je smartphone om je gemiddelde schermtijd te bekijken (afhankelijk van het type telefoon, kan het verschillen waar je dit precies kunt vinden).

Q5 Please state the amount of time you expect to spend on social media during the next 7 days (starting tomorrow):

Geef aan hoeveel tijd je de komende 7 dagen verwacht te besteden aan sociale media (vanaf morgen):

- ◯ Hours/Uur (1) ____
- ◯ Minutes/Minuten (2) ____

Page Break

Q6 Please state the amount of time that would be your personal ideal time to spend on social media during (the next) 7 days:

Geef aan hoeveel tijd jouw persoonlijke ideaal zou zijn om aan sociale media zou besteden gedurende (de komende) 7 dagen:

- ◯ Hours/Uur (1) ____
- ◯ Minutes/Minuten (2) ____

End of Block: Default Question Block

Start of Block: Block 1 **(each participant randomly assigned either Block 1 or Block 2)**

Now imagine that there would be an application that you can install on your phone that could restrict your screentime. With this application, you can lock either your entire phone (you will still be able to make calls, for example in case of emergency) or a particular app for a self-determined time. During this time, you are unable to receive notifications on your phone or from this particular app and you are unable to open the app itself. After the set time is over, your phone will go back to normal.

Stel je voor dat je een applicatie kunt downloaden die schermtijd beperkt. Deze applicatie kan je volledige telefoon blokkeren (exclusief noodtelefoontjes), of kan een bepaalde app blokkeren voor een zelf-ingestelde tijd. Gedurende deze tijd ontvang je geen notificaties van deze app en is het niet mogelijk de app te openen. Na de ingestelde tijd zal de telefoon terugkeren naar normaal.

Q7 On a scale of 1 to 10, how attractive does this application sound to you?

Op een schaal van 1 tot 10, hoe aantrekkelijk vind je deze applicatie klinken?

	1	2	3	4	5	6	7	8	9	10
Attractiveness										

Q8 On a scale of 1 to 10, how likely would you be to install and use this application?

Op een schaal van 1 tot 10, hoe waarschijnlijk is het dat je deze app zelf zult installeren en gebruiken?

	1	2	3	4	5	6	7	8	9	10
Likelihood of use										

Page Break

Please enter your e-mail address to receive the second part of this survey in seven days. Please know that your e-mail address will only be used to send you the second part of the survey, and will be deleted immediately after the second survey is completed. Your e-mail address will not be connected to your results, your first and second survey will be connected via a randomly generated code.

Vul hier je e-mailadres in om over zeven dagen het tweede deel van deze enquête te ontvangen. Het e-mailadres zal enkel gebruikt worden om het tweede deel van de enquête toe te sturen, en zal direct worden verwijderd na het afronden van de tweede enquête. Het e-mailadres wordt niet gekoppeld aan jouw resultaten, de twee delen van de enquête worden via een unieke, willekeurige code aan elkaar gekoppeld.

○ E-mail address (1) ____

End of Block: Block 1

Start of Block: Block 2

Please enter your e-mail address to receive the second part of this survey in seven days. Please know that your e-mail address will only be used to send you the second part of the survey, and will be deleted immediately after the second survey is completed. Your e-mail address will not be connected to your results, your first and second survey will be connected via a randomly generated code.

Vul hier je e-mailadres in om over zeven dagen het tweede deel van deze enquête te ontvangen. Het e-mailadres zal enkel gebruikt worden om het tweede deel van de enquête toe te sturen, en zal direct worden verwijderd na het afronden van de tweede enquête. Het e-mailadres wordt niet gekoppeld aan jouw resultaten, de twee delen van de enquête worden via een unieke, willekeurige code aan elkaar gekoppeld.

○ E-mail address (1) ____

End of Block: Block 2

Social media, part 2

Start of Block: Default Question Block

Dear participant,

Thank you for participating in this study on the use of social media. This research is conducted via the Erasmus University for a Bachelor thesis on the use of social media. All your answers are completely confidential and cannot be traced back to you. Participation is voluntary and data collection will be anonymous. The data will be used purely for research purposes and will be deleted four weeks after the completion of the research. This is the second part of this study.

Beste deelnemer,

Hartelijk dank voor uw deelname in deze studie over social media gebruik. Deze studie zal worden gedaan via de Erasmus Universiteit Rotterdam. Alle antwoorden worden vertrouwelijk verwerkt. Deelname is vrijwillig en dataverzameling is anoniem. Alle data wordt enkel gebruikt voor onderzoeksdoeleinde en worden vier weken na het voltooien van de studie verwijderd. Dit is het tweede onderdeel van dit onderzoek.

Q1 Please fill in the unique code found in the invitation e-mail.

Vul hier de unieke code uit de uitnodigingse-mail in.

____

End of Block: Default Question Block

Start of Block: Block 1

This survey is about the time you spend on social media. We define social media as media technology that facilitates the sharing of ideas, thoughts and information through the building of virtual networks and communities. Examples of such media are Facebook, Twitter and Instagram, but also WhatsApp and LinkedIn. To answer the next question, you can go to ‘Settings’ on your smartphone to view your average or past screentime (depending on your type of phone, it might differ where exactly you can find this). Please also add any time you spent on social media using different devices than your phone.

Deze enquête gaat over de tijd die je aan sociale media besteedt. Onder social media zien we media voor het delen van ideeën, gedachten en informatie doormiddel van het bouwen van online netwerken en communities. Hieronder vallen Facebook, Twitter en Instagram, maar ook media als Whatsapp en LinkedIn. Om de volgende vraag te beantwoorden, kun je naar 'Instellingen' gaan op je smartphone om je gemiddelde schermtijd te bekijken (afhankelijk van het type telefoon, kan het verschillen waar je dit precies kunt vinden). Tel hier ook tijd die je hebt besteed aan social media op andere apparaten bij op.

Q2 Please state the amount of time you *actually* spent on social media during the past 7 days.

Geef aan hoeveel tijd je de afgelopen 7 dagen *daadwerkelijk* hebt besteed aan sociale media:

○ Hours/Uur (1) ____

○ Minutes/Minuten (2) ____

Q3 Do you think this corresponds to the amount of time you predicted one week ago?

Denk je dat dit overeenkomt met de tijd die je vorige week hebt voorspeld?

○ Yes/Ja (1)

○ No/Nee (2)

End of Block: Block 1

Start of Block: Block 2

Now imagine that there would be an application that you can install on your phone that could restrict your screentime. With this application, you can lock either your entire phone (you will still be able to make calls, for example in case of emergency) or a particular app for a self-determined time. During this time, you are unable to receive notifications on your phone or from this particular app and you are unable to open the app itself. After the set time is over, your phone will go back to normal.

Stel je voor dat je een applicatie kunt downloaden die schermtijd beperkt. Deze applicatie kan je volledige telefoon blokkeren (exclusief noodtelefoontjes), of kan een bepaalde app blokkeren voor een zelf-ingestelde tijd. Gedurende deze tijd ontvang je geen notificaties van deze app en is het niet mogelijk de app te openen. Na de ingestelde tijd zal de telefoon terugkeren naar normaal.

Q4 On a scale of 1 to 10, how attractive does this application sound to you?

Op een schaal van 1 tot 10, hoe aantrekkelijk vind je deze applicatie klinken?

	1	2	3	4	5	6	7	8	9	10
Attractiveness										

Q5 On a scale of 1 to 10, how likely would you be to install and use this application?

Op een schaal van 1 tot 10, hoe waarschijnlijk is het dat je deze app zelf zult installeren en gebruiken?

	1	2	3	4	5	6	7	8	9	10
Likelihood of use										

End of Block: Block 2