

# Digital Addiction\*

## Analysis of How Usage of Social Media Impact Objective Well-Being And Political Opinion

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The global population of social media users is predicted to reach 4.95 billion by 2023; this is a significant increase from the 2.05 billion users in 2015 (source: Backlinko). As technology continues to evolve, smartphones are playing an increasingly important role in our daily lives, providing us with more and more services. However, the impact of smartphones on our lives still needs to be further explored. In this paper, we will discuss two aspects. First, we explore the impact of the social media Facebook on social and political attitudes, providing insights and calling for further research on interventions to mitigate its negative effects. The paper analyzes experimental data related to subjective well-being by experimentally surveying participants and using an analytic factorial design to randomize them into reward and restriction groups. The study uses regression modelling to assess the impact of specific digital technology use patterns on well-being. We also examine whether Facebook use affects people's political attitudes.

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\*Code and data are available at: [https://github.com/YO7O/digital\\_addiction.git](https://github.com/YO7O/digital_addiction.git)

## 1 Introduction

In 2023, there will be more than 4.95 billion users of different social media across the world. It has rapidly increased since 2015, as it only had 2.05 billion social media users at that time. (backlinko) According to Datareportal, in quarter 3 of 2021, it shows 46% of Americans spend 4 to 5 hours every day on their phones and 1 in 5 people have more than 4.5 hours per day of usage of their phone. With the development of technology, smartphones have started to offer more services and play a more important role in daily life. However, how the smartphone impacts our lives need more exploration for it. Based on this background, we will have discuss it from two aspects.

Regarding our first argument, the article provides very valuable insights into the complexity of digital addiction and its impact on individuals and society, urging further research interventions to mitigate its negative effects. The authors discuss and analyze experiments related to subjective well-being. They administered four surveys to participants between April 12th and June 14th. Participants were randomized into rewarding and limiting treatment conditions using an analytic factor design. A participant-led experimental intervention known as the restriction group may have been a part of this. In order to evaluate the impacts of particular digital technology usage patterns on their well-being, experiments estimate treatment effects using regression models that include restriction and reward group indicators. These studies might compare the well-being levels of individuals who use various digital technologies, or they can monitor changes in participants' well-being before and after using digital technology. In research pertaining to mobile phone usage, control and restriction groups can be employed to evaluate the effects of interventions on cell phone use as well as the effects of cell phone use on an individual's behaviour or psychological state.

Our paper is followed by a reproduction of Hunt Allcott, Matthew Gentzkow, and Lena Song's analysis(Allcott, Gentzkow, and Song 2022) of digital addiction to social media and their experiments prove reducing the usage of social media incentive new habits. Furthermore, their model shows that self-control is one of the important problems for people and it causes 31 percent of social media use.

In our paper, we use a dataset for users who most focus on using Facebook as social media. The experiment has two periods which are baseline and endline. The research target is separate into control and treatment groups, for the control group, they can themselves and for the treatment group they can get treatment if they achieve goals about self-control for using social media. At the beginning of the experiment, the research targets finish a survey about how their mental health works at that time and other information like political trends and knowledge they get from the news. After four weeks, both groups of research targets wrote the survey and it shows there are differences between them. Both groups have a significant change for baseline and end line. The control group have a worse performance than the treatment group.

## 2 Data

### 2.1 Methodological Approach

The authors in their experiment mainly adopted the standardized measures from the subjective well-being literature, where the respondents were required to answer the following seven questions of a questionnaire after conducting different groups of rules each week, Over the last three weeks,” with a matrix of six questions, based on the different responses it is possible to categorize and collect new data.

### 2.2 Survey Measures:

The research includes several variables related to social media and examines the effects of different groups of experimenters in experiments with different time regimes for social media use. The nature and severity of digital addiction are relevant to many important issues, and the authors adopted economic models of digital addiction, using randomized experiments to provide unmodeled evidence and estimate model parameters that would simulate the effects of habit formation and self-control issues on smartphone use, and these valuations would also directly affect the experimenter’s reference data.

### 2.3 Tool

Our paper use data from While writing the paper, we have utilized different tools and literature references to ensure that the findings across the board were correctly logical. Our graphs and data analysis plots were laid using R code(R Core Team 2023) as a base. library tidyverse(Wickham et al. 2019) directly helped us to start from the data so that we can process and visualize the data for application in no time. library haven(Wickham, Miller, and Smith 2023) to help us quickly convert the data we need into R language format. It can be convenient for us to import data into R for analysis and processing. library readxl(Wickham and Bryan 2023) helps us read some Excel functions and processing. This makes it easier for us to analyze Excel data in R. library janitor(Firke 2023) helps us to check and clean up the dirty data, and format the data we need in R. library ggpubr(Kassambara 2023) facilitates us to draw graphs to meet the research direction more easily. These tools help us to understand more deeply the direction of the research and the relationship between them.

## 3 Result

These figure(Figure 1) show the distribution of Facebook usage at Baseline and Endline. The red is the control group and the green is the treatment group. The Y-axis shows the fraction of the sample and the x-axis shows Facebook usage time. For the longest time, the endline

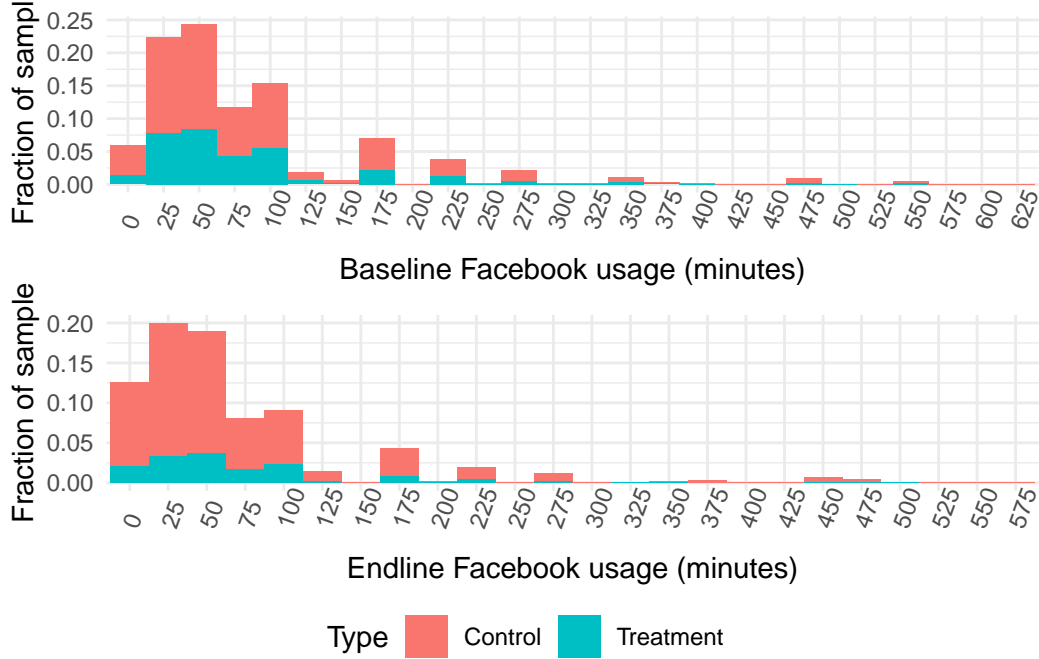


Figure 1: Facebook Usage Time at Baseline And Endline

group's time is shorter than the baseline's time and the longest time both happen in the control group. The longest time for the treatment group is 550 minutes in baseline and 450 minutes in the endline group. For the treatment group, it decreases from 625 minutes to 575 minutes. To this result, there is a large decrease for the longest usage time. For the baseline, usage time exceeding 250 minutes is more than 2.5% in total but compared with it, at the endline, for the control group it has around 5% and for treatment is only 1.25%.

It is obvious that between 0 and 125 minutes, the figure has a skew left and generally fraction decreases for each period in the treatment group.

Above figure(Figure 2) shows dot plots that count the differences between two different groups in all directions of the survey, and explains the results of the control and treatment groups in the Subjective Well-Being of the survey. In this graph, the x-axis is the difference from the baseline, the y-axis is the subjective well-being, the orange line is the control group, the blue line is the treatment group, and the confidence interval is 95%. The treatment group was controlled by the researcher for the amount of time spent on Facebook per day and was rewarded accordingly for being controlled. The research target also generally responded that receiving the reward mechanism could greatly improve their subjective well-being. In contrast, there was not much change in the other survey directions. From the figure we can also see that the difference between the values of happiness, and conditions of life is excellent is not big, they are all concentrated in the range of -0.25 to 0.25. The subjective happiness of the treatment group will be a little bit lower than that of the control group at this time.

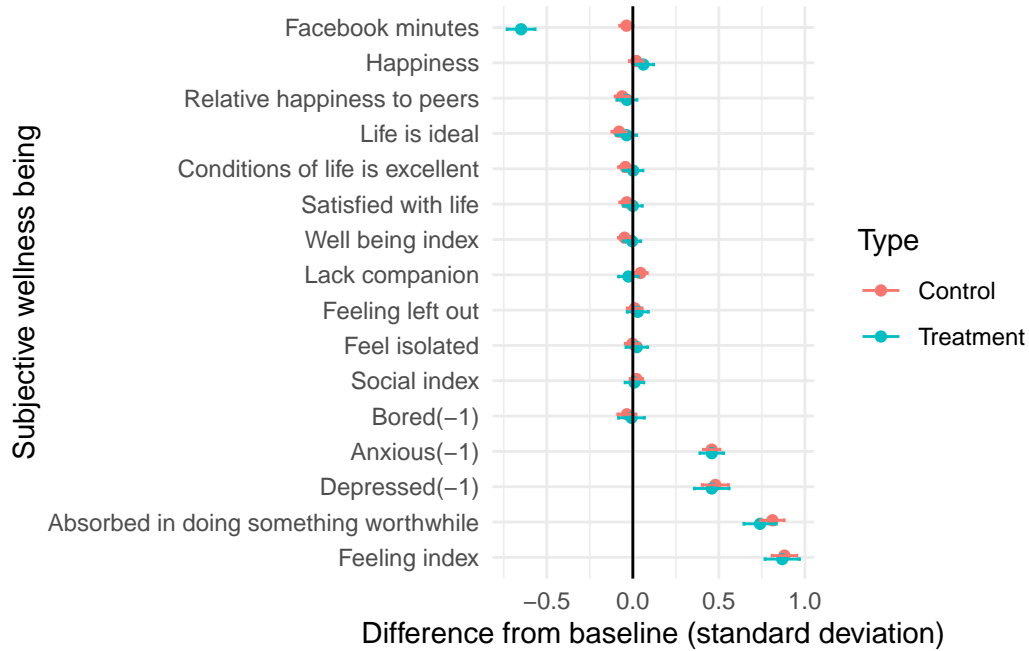


Figure 2: Difference at Baseline for Subjective Well-Being

The graph above shows the result of deactivation of the first 4 weeks, treatment means there is bonus cash if they successfully deactivate for another 4 weeks (8 weeks in total)

- Unit is the standard deviation of the baseline
- Well being an index is the sum of (Happiness, ... and satisfaction with life)
- The social index is the sum of (Lack companion, ..., Feel isolated)
- The feeling index is the sum of (Bored, ..., Absorbed in doing)

The above figure(Figure 3) show whether Facebook usage makes social life worse or better. The x-axis is formed from -6 to 6 which is based on a set of marking schemes for the research target to scale. From the figure, it has changed between -1 and 1. At baseline, it has the most fraction at 0 for the treatment group and in the control group, it has the most in -1 and 0. However, in endline's figure, the biggest fraction shifts to the right. It becomes 0 and 1. This means that user feels their social life becomes better. This helps to prove that with less time spent on Facebook, people's objective well-being increases.

This graphs(Figure 4)(Figure 5) shows whether people change their political stance when using Facebook or not. The two different political positions are Republican, Democrat or Independent and Liberal or Conservative. obviously, we can see from the Republican graph that most people would still strongly choose Strongly Democratic, almost to 0.3 The distance is almost 0.3. In the Liberal graph, we can see that most people would choose liberal over extremely liberal, with a figure of more than 0.3. So from this graph social media affects a lot of people who are liberal and conservatives are in the minority.

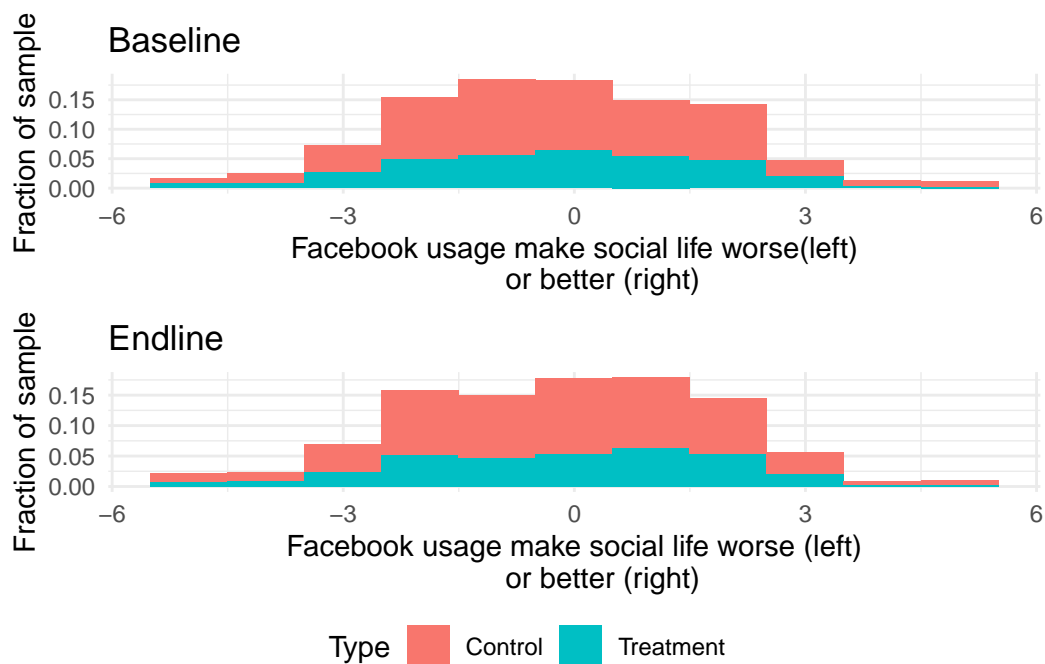


Figure 3: Facebook Make Social Life Worse or Better at Baseline And Endline Period

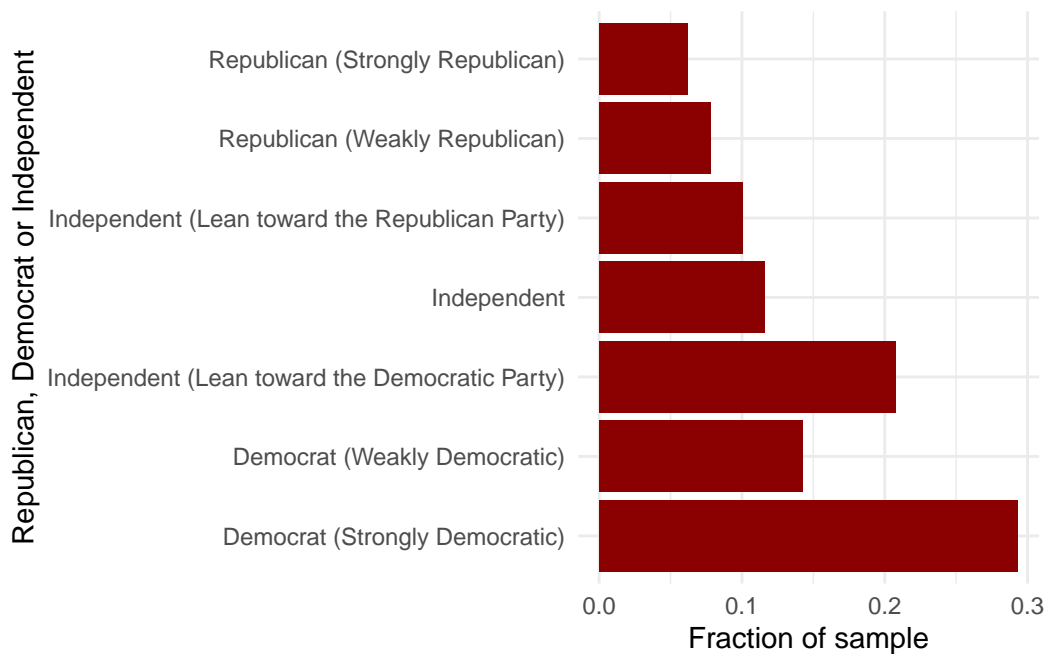


Figure 4: People Political Opinion 1

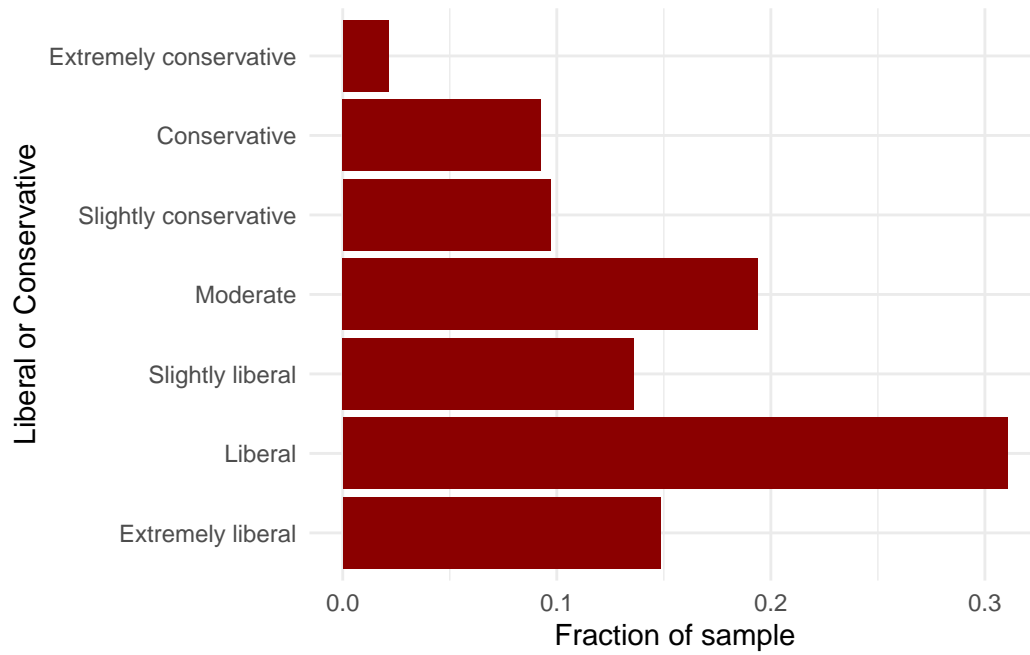


Figure 5: People Political Opinion 2

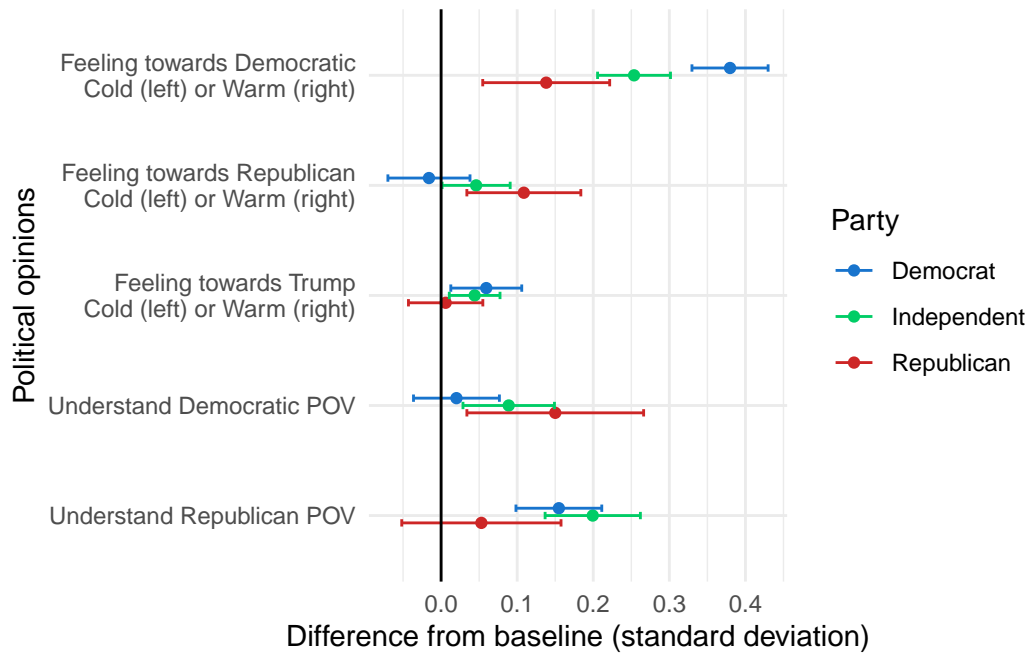


Figure 6: figure 6 cap

## 4 Discuss

In recent years, the popularity of smartphones has greatly increased the use of social media. Social media, as a communication tool, works in the context of people's interactions, and the psychological changes induced by interpersonal interactions become the mediating variable between its use and well-being. Excessive use of social media has a negative impact on health and well-being. Our present investigation suggests that limiting the time spent on social media use may be beneficial to health and well-being. Research has noted a correlation between reduced social media use and improved mental health, and this latest controlled experiment provides further evidence of a causal relationship between reduced social media use and improved physical health. For those who were directly asked to reduce their social media use time and do something else with that time, they did not experience health benefits, suggesting that if one wants to get a person healthier to exercise, one should not ask them how to use their time, which can be counterproductive.

There are some weaknesses of our experiment, that make our experiment lack generality. People in different age groups have different lifestyles and not all age groups have the same free time to use Facebook. For example, for seniors, some of them not familiar with smartphones and they do not understand how to use Facebook. Therefore, when they join the experiment, the experiment does not work as significantly as researchers expect. Also, different age groups can not have a more specific discussion about the actual situation of how people use Facebook. For example, Facebook is popular with people aged around 18-25 and those people, have more free time than people who have work, especially during summer vacation. This causes the experiment can not have generality.

In the future, researchers can have a longer experiment and track the research target after finishing the experiment to see did they kept the habit that they had at the endline or if they increased usage time. With this tracking, the researcher can check what difference between the control group and the treatment group, and then check if there are any direct relations to show which group has self-control. Therefore, researchers can know did their experiment impacted the research targets' lifestyles. Another thing, research can do to improve the experiment is to set different age groups thus, researchers can focus on how different age groups work and explore why there are differences between groups.

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