From Past Abiding Behavior to Subsequent Intervention Compliance: A Phone Usage Study

Rong Ji, Yang Meng, Zeyue Zhang

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Abstract

This study explores the impact of self-regulatory behaviors on students' compliance with interventions regarding mobile phone usage. Over three months, students' mobile interactions were tracked, followed by a one-week intervention where specific mobile usage constraints were enforced. The analysis focused on whether early morning discipline (e.g., attending early class, abiding by schedules) was linked to adherence to these limits. The hypothesis suggested that higher adherence to the predefined ordinances would result in higher compliance rates during the intervention period. Our logistic regression model supported this hypothesis. Furthermore, our investigation revealed that phone usage from the previous day — in terms of both screen time in minutes and pickup numbers — was significantly correlated with compliance in interventions. These findings suggest that students with higher self-discipline, who are more likely to follow rules, are expected to adhere more closely to imposed interventions.

Keywords: screentime data, cohort study, multiple imputation, logistic regression, treatment effectiveness;

1 Introduction

1.1 Objective

Mobile phone addiction is a significant concern among college students, given the rapid advancement of digital technology. Excessive mobile phone use can lead to various mental, psychological, and physical health issues [1]. While several behavioral interventions have been developed to curb mobile device addiction, there is a crucial need to assess their effectiveness. Specifically, it is important to examine participants' adherence to the interventions and identify potential factors that may influence their ability to meet the intervention goals. Therefore, this paper aims to investigate both compliance and the impact of an intervention program (environmental modification) designed to reduce mobile phone usage. The intervention program was implemented among a group of college students over the past three months, and details of the experimental design and data collection will be covered in the Section 1.2.

1.2 Study Design & Interventions

The study focuses on a cohort of 34 students who are all enrolled in BIOSTAT 620, a health data science class that meets at 8:30 every Tuesday and Thursday. Starting in mid-January, students were asked to record their screen time usage statistics (e.g., screen time, phone pickups) daily on their phones. They did not receive any behavioral intervention during this period, allowing them to use their phones based on their habits and preferences until March 27. On March 27, each student was randomly assigned to one of two intervention categories: Intervention A aimed to limit daily mobile phone usage to 200 minutes, while Intervention B set a cap of 50 phone pickups per day. The interventions were implemented over a week, from March 27 to April 2. During this intervention period, in addition to documenting their screen time usage as usual, students were asked to record their compliance (success coded as 1, failure as 0) of accomplishing the allowed phone usage limit based on their intervention category. Personal background information, such as age and gender, was also collected as baseline variables. A detailed overview of the full list of screen time usage statistics and baseline variables will be provided in the Section 2.1 and Appendix Table 4.

1.3 Hypothesis

Our objective is to investigate potential factors influencing compliance with the intervention task. We consider that procrastination, a common issue associated with mobile phone addiction, may contribute to non-compliance [2]. However, we aim to utilize the pre-treatment data to predict compliance rates during the intervention period. To achieve this, we have created new variables derived from the pre-intervention data. These variables, including one called `"early"`, which measures a student's attendance and punctuality for early morning classes, are detailed in Section 3.1. We believe that the `"early"` variable reflects a student's self-discipline, goal orientation, and obedience tendencies, and it should be significantly associated with compliance possibility during the intervention period. Our hypothesis, stated as $H_0 : \beta_{\text{early}} = 0$ versus $H_1 : \beta_{\text{early}} \neq 0$, will be tested in Section 4.

2 Data Description

2.1 Description of Variables

The original dataset is an Excel file with two sheets: `"screentime"` and `"baseline"`. The `"screentime"` sheet contains phone usage activity data for each participant from early January (the exact starting time varied by person) to April 2, 2024, collected directly from their phones. The `"baseline"` sheet contains features used to characterize individuals, recorded by participants answering a series of questions. After merging the two sheets using `"pseudo-ID"`, the current dataset comprises 2672 observations and 27 variables. A more detailed list of variables and descriptions is available in Appendix Table 4. The first 13 variables of the Table 4 belong to the `"screentime"` sheet and the remaining 14 variables pertain to `"baseline"` sheet. We also supplied descriptive statistics of the study cohort in Appendix Table 5 and Table 6 as well as some density plots for the selected variables between genders in Appendix Figure 7.

2.2 Parameter of Interest

In this study, as previously stated, our primary outcome of interest is the variable `"compliance"`, the probability of complying with the assigned intervention rules. Our predictor of interest is the newly defined variable `"early"`. Additionally, we are interested in including other measurement values in our model, such as the procrastination score, the lag-1 effect of yesterday's observation (discussed in 3.1), and the average mobile phone usage from the last three weeks (discussed in 3.1) before accepting the intervention. The following Sections 3 and 4 will provide further components on data cleaning, variable creation, and model fitting.

3 Data Preprocessing

3.1 Quality Control & Cleaning & Processing

The primary goal of this subsection is to illustrate the necessary procedures we need to perform before conducting data analysis in Section 4, including checking quality control, detecting outliers, and defining new variables based on our research question.

(**Quality Control**) The main quality control categories include *invalid data*, *data inconsistency*, *data accuracy*, *data precision*, and *data missing*. Regarding *invalid data*, it is essential to verify if the measurements of our variables fall within valid ranges. For instance, we should anticipate that the daily total screen time (in minutes) is a non-negative value and falls within the interval $[0, 1440]$. Similarly, the score for a procrastination test should range between 0 and 100. *Data inconsistency* is a primary issue in our dataset, as many variables are not recorded in the same unit. For example, some participants record their daily screentime usage in hour-minute units, necessitating the normalization of these values into minute units. Another case is the binary variable *compliance* which takes values between 0 (Fail) and 1 (Success), indicating whether a participant accomplished the assigned intervention task in the last 7 days. However, some entries are recorded as "Yes" "No" "Success" or "Fail" in the dataset, requiring conversion to 1 or 0 respectively. Additionally, at the start of the semester, some participants might have disabled their phones to collect screen time statistics, potentially leading to the under-reporting of information during that period and raising concerns about *data accuracy*. Furthermore, some participants may tend to report lower screen time usage than the actual amount, which could impact the *data precision*. Therefore, caution is advised when interpreting the outcomes after obtaining the results in Section

4.2. Finally, *data missing* is still present, and we will address this through imputation in Section 3.2 and evaluation of the imputation results in Section 4.3.

(**Outliers**) The focus of outlier detection is to identify data points that are significantly distant from the main body, typically done for continuous variables. In the original dataset, daily total screen time (in minutes) and daily number of pickups are two features most likely to have outliers, as shown in the Boxplot Figure 1 below. From the Boxplot 1, we observe that some entries had daily total screen times exceeding 1200 minutes (equivalent to 20 hours per day), which is unrealistic. Additionally, there are observations with daily pickups exceeding 300 times, which is also abnormal. To determine whether these outlier points should be removed, we conducted the with-and-without outliers analysis based on the mean calculation formula $(\bar{x}_0 - \bar{x})/\sqrt{\mathrm{Var}(x)}$ where $\bar{x}_0$ is the mean of the original data and $\bar{x}$ is the mean of the data without outliers points. If the results show minimal change, the outliers are of minor concern. Both analyses in our case resulted in absolute values less than 0.05, indicating that these outliers have a minor impact on the mean estimation.

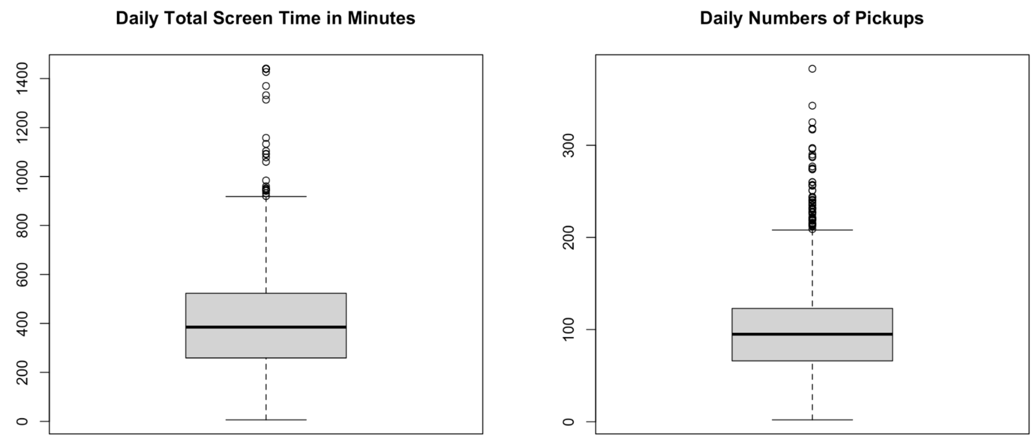

Figure 1: Boxplots of Daily Total Screen Time (in Minutes) & Daily Pickups Numbers

(**Variables Creation**) Based on the original variables introduced in Section 2.1, we also created additional variables that we believe may help capture the objective of our question. We divided the data into two subsets based on treatment categories. One subset (referred to as `data_A`) includes all observations for participants assigned to intervention A (allowance of 200 total screen time minutes per day), while the other subset (referred to as `data_B`) includes observations for participants assigned to intervention B (allowance of 50 pickups per day). We then generated three new variables for each subset of data and descriptions of newly defined variables are provided below. For `data_A`:

- `lag_y1`: representing yesterday's total screen time (in minutes) for each user. Since this is longitudinal data, defining the `lag_y1` variable (lag-1 effect) enables us to capture the temporal dependence between daily total screen time or to show the association between observations measured today and those in yesterday.

- `early`: portraying the proportion of each participant's daily first mobile phone pick-up time no later than 8:00 AM in a given period, which is defined as Tuesday and Thursday from March 5 to March 26, totaling 7 sessions (4 Tuesdays and 3 Thursdays). Tuesday and Thursday were chosen because all participants have BIOSTAT 620 (starting at 8:30) on these two days each week. We expect all participants to pick up their phones before 8:00 AM during these 7 days, as they are expected to get up on time and attend class punctually at 8:30 AM. A 30-minute gap is supposed for necessary personal affairs (e.g., eating breakfast, commuting) before arriving at the classroom. For instance, if a person's first pick-up time is earlier than 8:00 AM on 3 days out of these 7, we set their `early` variable as 3/7; if it's on all 7 days, we set it as 7/7=1. A higher `early` value implies the person is more likely to accomplish tasks as planned (e.g., attending class on time). One reasonable guess may be the person is more likely to be self-disciplined and may have a higher chance of complying with intervention rules from March 27 to April 2. Conversely, a lower `early` value indicates a person is more likely to be sluggish (e.g., failing to attend class on time regularly). One may argue the person is less likely to follow prescriptive regulations and may with a lower chance of compliance later during the intervention. The three weeks from March 5 to March 26 can be considered as baseline data, preceding the treatment intervention (from March 27 to April 2). Defining the new abiding behavior variable `early` grants us an approach to interpret how pre-treatment behavior may influence compliance probability during the treatment period.

- `base_mean`: depicting the mean daily total screen time (in minutes) for each participant, based on records from March 5 to March 26 (pre-intervention period), the new variable `base_mean` allows us to retain pre-intervention phone usage data in our analysis. It also helps us to investigate the potential association between pre-intervention average daily screen time (in minutes) and the likelihood of compliance (maximum of 200 minutes per day) during the intervention interval.

For `data_B`:

- `lag_y2`: representing yesterday's number of pickups for each user. Since this is longitudinal data, defining the `lag_y2` variable (lag-1 effect) enables us to capture the temporal dependence between the daily number of pickups or to show the association between observations measured today and those in yesterday.
- `early`: same as the `early` variable define above in `data_A`.
- `base_mean`: depicting the mean daily number of pickups for each participant,

based on records from March 5 to March 26 (pre-intervention period), the new variable `base_mean` allows us to retain pre-intervention phone usage data in our analysis. It also helps us to investigate the potential association between the pre-intervention average daily number of pickups and the likelihood of compliance (maximum of 50 pickups per day) during the intervention interval.

It is worth noting that the values of the newly defined variables mentioned above are derived from the existing variables discussed in Section 2.1. Given that the original variables contain missing values, it is anticipated that the newly created variables may also have missing data in some observations. We will address this issue using the imputation techniques outlined in Section 3.2.

3.2 Missing Data Imputation

In this subsection, we explored the multiple imputation procedure for handling missing data using the R-package MICE. MICE offers multiple imputations for multivariate missing data, employing a fully conditional specification approach where each incomplete variable is imputed by a separate model considering all other variables. The mice() function within the MICE package enables missing data imputation. In our study, we remained default argument `"m=5"` in the mice() function, indicating the number of imputed datasets as 5. Additionally, we configured the argument `"method=pmm"` since our variables with missing values are continuous variables (e.g., daily total screen time, number of pickups). The two lines of code below should generate and return all five imputed datasets from `data_A`. To produce and report the imputed datasets for `data_B`, simply replace `data_A` with `data_B`. It is advisable to include `"set.seed()"` at the beginning of the code to ensure reproducibility and replicability, as each run will otherwise generate imputed datasets with different filled-in values.

```
data_A_mice<-mice(data_A, method="pmm", m=5)
```

```
complete_A <-complete(data_A_mice, "all")
```

After obtaining the imputed datasets, we conducted an after-imputation analysis for estimation and inference, and the specifics are detailed in Sections 4.1, 4.2, and 4.3.

4 Data Analysis

4.1 Logistic Regression Model

The objective of this subsection is to illustrate the model construction of our data analysis as well as the model fitting process. As mentioned earlier in Section 2.2, the outcome in our study is `compliance`, a binary variable that takes values between 0 (Fail) and 1 (Success), so we decided to implement a logistic regression model. The model included newly defined abiding behavior variables (`early`, `base_mean`, `lag_y1` or `lag_y2`) introduced in Section 3.1 and the `score` variable introduced in Table 4. The model can be expressed as follows and π is the probability of achieving the allowed accessibility (successful compliance) for each person per day during the intervention treatment period.

Intervention A Model: $\texttt{logit}(\pi) = \beta_0 + \beta_1 \cdot \texttt{lag\_y1} + \beta_2 \cdot \texttt{base\_mean} + \beta_3 \cdot \texttt{score} + \beta_4 \cdot \texttt{early}$

Intervention B Model: $\texttt{logit}(\pi) = \beta_0 + \beta_1 \cdot \texttt{lag\_y2} + \beta_2 \cdot \texttt{base\_mean} + \beta_3 \cdot \texttt{score} + \beta_4 \cdot \texttt{early}$

Recall from Section 1.3, our hypothesis here for both models is $H_0 : \beta_4 = 0$ versus $H_1 : \beta_4 \neq 0$. In Section 3.2, we generated five imputed datasets using the `mice()` function and stored them in the variable `complete_A`, which is an array. To fit the model, we filtered the `complete_A` array to include only observations where `date` is between

2024-03-27 and 2024-04-02, as our response variable `compliance` is only present during the intervention treatment period (March 27 to April 2). We now have an array containing five imputed datasets, each containing observations from March 27 to April 2 for all individuals assigned to Intervention A. For each dataset, we fitted the **Intervention A Model**. The following line of code shows the fitted model (`"A1"`) using the first imputed dataset (`"data_A1"`) from the `complete_A` array.

```
A1<-glm(compilance=lag_y1+base_mean+score+early,data_A1,binomial("logit"))
```

Following the same approach, the second through fifth imputed data sets from `"complete_A"` are named `"data_A2"` through `"data_A5"`. Similarly, we could obtain fitted models from `"A2"` to `"A5"`. This process can be replicated for `"data_B"`, resulting in `"complete_B"`, corresponding `"data_B1"` to `"data_B5"`, and fitted models `"B1"` to `"B5"`. Ultimately, we have a total of 10 fitted models, 5 each for Intervention A and Intervention B, with results presented in the following Section 4.2.

4.2 GLM Results

From Section 4.1, we have ten fitted GLM models, and we exhibited the estimates and p-values of our predictor of interest β_4 in the Table 1 below. Due to space limit, we placed the summary of $\beta_1, \beta_2, \beta_3$'s estimates and p-values in the Appendix Table 8. We also used the `pool()` function, which combines the estimates from "m" repeated complete data analyses. We have provided the estimates and p-values for all β for each Intervention Model A and B in the following Table 2.

	Model 1	Model 2	Model 3	Model 4	Model 5
β_4 Estimate (A)	-0.85478	-2.00139	-1.36724	-1.93766	-1.35384
β_4 P-Values (A)	0.37459	0.07296	0.19951	0.07949	0.20869
β_4 Estimate (B)	-2.31619	-1.97896	-2.52193	-1.71969	-1.57729
β_4 P-Values (B)	0.00109	0.01981	0.00105	0.02150	0.01350

Table 1: Summary of β_4's Estimate & P-Values by 10 Fitted GLM Models

	β_0	β_1	β_2	β_3	β_4
Model A Estimate	4.94056	-0.01191	-0.00163	-0.03048	-1.41171
Model A P-Values	0.00011	$1.15544e^{-9}$	0.43219	0.28683	0.08939
Model B Estimate	2.20973	-0.03843	-0.00357	0.00288	-1.19256
Model B P-Values	0.02222	$3.11952e^{-9}$	0.70035	0.84552	0.03543

Table 2: Summary of β's Estimate & P-Values by Using `"pool()"` Function

From Table 1, 2, and 8, in the **Intervention A Model**, we found that all p-values were greater than 0.05, indicating a failure to reject the null hypothesis. We concluded that there is no evidence to support the statistically significant association between the pre-treatment behavior predictor β_4 and the probability of complying with the Intervention A assignment (maximum 200 minutes of screen time per day) for individuals in this cohort. Conversely, in the **Intervention B Model**, we observed that all p-values were less than 0.05, allowing us to reject the null hypothesis. We concluded that there is evidence supporting the statistically significant association between the pre-treatment behavior predictor β_4 and the probability of complying with the Intervention B assignment (maximum 50 pickups per day) for individuals in this cohort. For `"pool()"`'s β_4 in the **Intervention B Model**, we can interpret as $\exp(\beta_4) = 0.303$ is the increase in odds-ratio of having successful compliance for per unit increase in the pre-treatment behavior variable `"early"`, adjusting for all the other variables. We also caught yesterday's usage β_1 (lag-1 effect) was also significantly associated with the possibility of compliance in both models.

4.3 Missing Data Imputation Diagnostics

After generating imputed datasets from Section 3.2, we aim to evaluate the effectiveness of the imputation. Using the fitted GLM models from Section 4.1 and 4.2, we can calculate metrics to assess the performance of the imputation analysis. Following Rubin's rules [3], we generated five different imputed sets (`"m=5"`) and estimated the parameters $\hat{\theta}_i, i = (1, \cdots, m)$ based on the logistic regression model. Therefore, we have the between-imputation variances (**BIV**) as $B = \frac{1}{m-1}\sum_{i=1}^{m}(\hat{\theta}_i - \bar{\theta})^2$ where $\bar{\theta} = \frac{1}{m}\sum_{i=1}^{m}\hat{\theta}_i$ and average of within-imputation variances (**WIV**) as $\bar{W} = \frac{1}{m}\sum_{i=1}^{m} W_i$ where $W_i = \mathrm{var}(\hat{\theta}_i), i = (1, \cdots, m)$. Hence, the variances of $\bar{\theta}$ is the total variances (**TW**) as $T = \bar{W} + (1 + \frac{1}{m})B$. Then, the degrees of freedom (**DF**) is $v_m = (m-1)\{1 + \bar{W}/((1+m^{-1})B)\}^2$. Also, the relative increase in variances (**RIV**) due to non-response is $r = (1+m^{-1})B/\bar{W}$. Next, the fraction of missing information (**FMI**) about θ is $\lambda = (r + 2/(w_m + 3))/(r+1)$. Finally, the relative efficiency (**RE**) is $\mathrm{RE} = (1 + \lambda/m)^{-1}$. Details in Table 3 below.

	WIV	BIV	TW	RIV	FMI	RE
(A) `lag_y1`	$5.378e^{-6}$	$1.735e^{-7}$	$5.586e^{-6}$	0.039	0.0380	0.992
(A) `base_mean`	$6.320e^{-6}$	$4.735e^{-7}$	$6.889e^{-6}$	0.089	0.086	0.983
(A) `score`	$8.828e^{-4}$	$1.983e^{-5}$	$9.066e^{-4}$	0.027	0.027	0.995
(A) `early`	$1.138e^{-0}$	$2.245e^{-1}$	$1.407e^{-0}$	0.237	0.206	0.960
(B) `lag_y2`	$6.812e^{-5}$	$3.146e^{-6}$	$7.189e^{-5}$	0.0554	0.0538	0.989
(B) `base_mean`	$1.587e^{-4}$	$2.609e^{-6}$	$1.617e^{-4}$	0.0197	0.0195	0.996
(B) `score`	$3.661e^{-4}$	$2.621e^{-5}$	$3.975e^{-4}$	0.086	0.082	0.984
(B) `early`	$5.568e^{-1}$	$1.569e^{-1}$	$7.450e^{-1}$	0.338	0.275	0.948

Table 3: Imputation Diagnostics Information

The relative efficiency of an imputation assesses the accuracy of estimating true population parameters and provides an estimate of efficiency compared to an infinite number of imputations. From Table 3, RE is nearly 1 in both models, signifying that setting the number of imputed datasets to `"m=5"` is suitable for our data and study.

5 Conclusions & Discussion

The main finding of this study indicates that the pre-treatment abiding behavior variable `"early"` is significantly associated with complying with allowed phone usage in Intervention B. Additionally, we found that the previous day's phone usage (either screen time minutes or pickup time) is significantly associated with compliance with intervention assignment (A or B). The study also presents a comprehensive data science workflow encompassing experimental design, data collection and cleaning, and data analysis, with potential extensions in clinical studies and scientific inquiries.

Several limitations should be considered before generalizing our findings. The cohort study was relatively small, with only 34 participants. Although each participant had around 80 observations, some data were missing, and datasets with imputed values may raise concerns about data precision. Another limitation is that, due to the longitudinal nature of the data, we only considered a lag-1 transitional GLM model, suggesting that a more precise approach should incorporate longitudinal analysis.

Future research directions are promising. Instead of dividing the original data into subsets based on intervention categories, an alternative is to analyze the combined dataset with both Interventions A and B. Additionally, using the EM algorithm for missing data imputation could be more optimal than multiple imputation. Lastly, exploring dynamic treatment regimes could offer interesting avenues. Tailoring intervention options based on past data could personalize compliance policies, potentially optimizing long-term clinical outcomes such as reducing daily mobile phone usage, particularly for individuals with different usage patterns.

References

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The following is our GitHub link, everyone is welcome to learn and communicate: https://github.com/Lareina111/Biostat620-study-2

Appendix: Useful Tables & Figures

A Variables Description Table

Name	Description
pseudo_ID	ID number to represent each participant;
Date	date of observations throughout the Winter 2024 semester;
Day	day in week (from Monday to Sunday) corresponding to the date;
Total.ST	daily total screen time in hour-minute format;
Total.ST.min	daily total screen time in minute format;
Social.ST	daily total social app screen time in hour-minute format;
Social.ST.min	daily total social app screen time in minute format;
Pickups	daily total number of phone pickups;
Pickup.1st	daily first pick-up phone time after participant's morning wake-up;
Proportion.ST	daily proportion of social app screen time in total screen time;
Duration.per.use	daily screen time minutes by each time of pickup
Compliance	success (`"1"`) or failure (`"0"`) of complying the assigned intervention;
Treatment	A (200 minutes for total screen time); B (50 pickups for total pickups);
Workmate	number of teammates worked previously for any other group studys;
Academic	number of teammates talk regularly about academic matters;
Non-academic	number of teammates had ever talked to about non-academic matters;
Pets	whether live with pets at home (YES=1, No=0);
Sex	gender (Female=0, Male=1);
Age	age in years;
Course_Hours	course credit hours in the winter semester;
Degree	country where previous degree received (US=1, Non-US=0);
Job	whether currently have a job (> 10 hours/week) (Yes=1, No=0);
Siblings	number of siblings;
Apps	number of social apps installed on major mobile device that use regularly;
Devices	number of personal mobile devices possessed;
Score	a procrastination score based on an online test of 10 questions;
BMI	a metric of body mass divided by the square of the body height (kg/m^2);

Table 4: Variables Description for Original Full Data

B Descriptive Statistics

	0 (N=104)	1 (N=75)	Missing (N=2493)	Overall (N=2672)
Total.ST.min				
Mean (SD)	404 (190)	230 (266)	410 (216)	405 (218)
Median [Min, Max]	362 [70.0, 932]	158 [17.0, 1370]	392 [6.00, 1440]	387 [6.00, 1440]
Missing	15 (14.4%)	7 (9.3%)	165 (6.6%)	187 (7.0%)
Social.ST.min				
Mean (SD)	191 (105)	83.9 (69.5)	195 (137)	191 (135)
Median [Min, Max]	179 [10.0, 446]	71.0 [0, 389]	173 [0, 754]	169 [0, 754]
Missing	15 (14.4%)	7 (9.3%)	165 (6.6%)	187 (7.0%)
Pickups				
Mean (SD)	91.8 (45.7)	52.3 (37.4)	98.5 (47.6)	96.9 (47.8)
Median [Min, Max]	80.0 [30.0, 260]	42.5 [3.00, 160]	97.0 [2.00, 383]	95.0 [2.00, 383]
Missing	5 (4.8%)	3 (4.0%)	48 (1.9%)	56 (2.1%)
Pickup.1st				
Mean (SD)	0.282 (0.155)	0.300 (0.162)	0.288 (0.147)	0.288 (0.148)
Median [Min, Max]	0.324 [0, 0.490]	0.323 [0.00139, 0.575]	0.313 [0, 1.37]	0.313 [0, 1.37]
Missing	24 (23.1%)	26 (34.7%)	313 (12.6%)	363 (13.6%)
Proportion.ST				
Mean (SD)	0.519 (0.150)	0.337 (0.204)	0.454 (0.213)	0.453 (0.212)
Median [Min, Max]	0.494 [0.230, 0.801]	0.324 [0.0751, 0.672]	0.457 [0.00755, 1.01]	0.457 [0.00755, 1.01]
Missing	82 (78.8%)	55 (73.3%)	1744 (70.0%)	1881 (70.4%)
Duration.per.use				
Mean (SD)	4.35 (3.11)	27.1 (63.1)	5.30 (4.77)	5.77 (10.9)
Median [Min, Max]	3.30 [1.59, 14.1]	4.32 [0.578, 273]	3.91 [0.717, 47.1]	3.89 [0.578, 273]
Missing	75 (72.1%)	55 (73.3%)	1671 (67.0%)	1801 (67.4%)
Treatment				
A	50 (48.1%)	50 (66.7%)	1089 (43.7%)	1189 (44.5%)
B	54 (51.9%)	25 (33.3%)	1404 (56.3%)	1483 (55.5%)

Table 5: Descriptive Statistics for Screen Time Usage Variables by `"Compilance"`

C Descriptive Statistics

	Score	Devices	Apps	Siblings	Age	Credit	Sex	Degree	Job	Pets
Median	37	3	3.5	0	23	14				
Min	16	1	1	0	21	0				
Max	58	5	10	7	31	17.5				
Std	11.59	1.06	1.99	1.76	1.75	3.34				
Missing	15%	15%	18%	18%	12%	15%	18%	15%	18%	12%
% of 1							0.64	0.41	0.29	0.07

Table 6: Descriptive Statistics for Baseline Variables

D Data Visualization

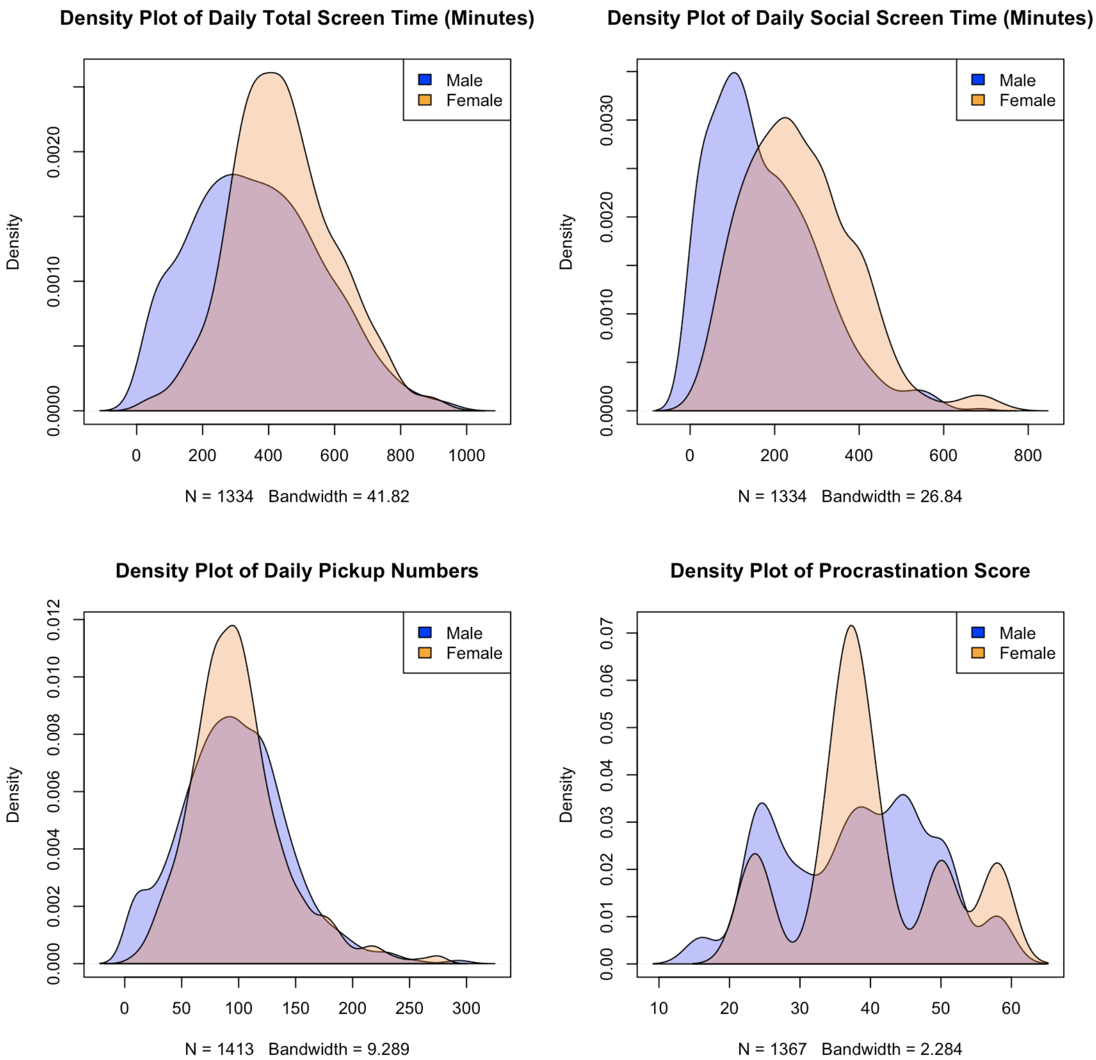

Table 7: Density Plots for Selected Variables Between Gender

E Summary of $\beta_0, \beta_1, \beta_2, \beta_3$ From 10 GLMs

	Model 1	Model 2	Model 3	Model 4	Model 5
β_0 Estimate (A)	3.27887	5.07687	4.23275	4.63542	3.97173
β_0 P-Values (A)	0.00917	0.00102	0.00403	0.00133	0.00396
β_1 Estimate (A)	-0.00962	-0.00956	-0.00925	-0.00917	-0.00857
β_1 P-Values (A)	$8.33e^{-5}$	$7.4e^{-5}$	0.00010	$3.98e^{-5}$	$4.9e^{-5}$
β_2 Estimate (A)	-0.00169	-0.00301	-0.00314	-0.00335	-0.00228
β_2 P-Values (A)	0.50514	0.26831	0.21279	0.16314	0.33717
β_3 Estimate (A)	0.01402	0.00429	0.01124	0.01426	0.00669
β_3 P-Values (A)	0.64894	0.89211	0.69183	0.63089	0.81055
β_0 Estimate (B)	3.61215	3.75969	3.98505	3.58589	2.88589
β_0 P-Values (B)	0.01395	0.02040	0.00958	0.02280	0.03680
β_1 Estimate (B)	-0.02162	-0.02320	-0.023045	-0.01937	-0.01983
β_1 P-Values (B)	0.00970	0.00605	0.00666	0.01500	0.01310
β_2 Estimate (B)	-0.01351	-0.01038	-0.01312	-0.01399	-0.01096
β_2 P-Values (B)	0.28605	0.39914	0.30298	0.28160	0.37170
β_3 Estimate (B)	0.00326	-0.00801	0.00047	-0.00809	0.00128
β_3 P-Values (B)	0.86756	0.66759	0.98094	0.66860	0.94610

Table 8: Summary of $\beta_0, \beta_1, \beta_2, \beta_3$'s Estimate & P-Values by 10 Fitted GLMs