Investigating both compliance and effect of intervention program on behavioral changes of mobile device use using generalized linear models

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1 Abstract

Our project mainly focused on investigating both compliance and effect of intervention program via the environmental modification approach on behavioral changes of mobile device use activities through an experiment among students.[2] We have constructed two generalized linear models. The first one explores whether course credits affect compliance. The second model investigates whether the intervention program reduces the number of pickups. Based on the results, we can determine course credits would have an impact on compliance, the more course credits would lead to a decrease in the success rate of compliance. The intervention program would also affect the number of pickups. Based on the result, the intervention would decrease the number of pickups per day.

Key Phases: Logistic regression, the number of pickups, intervention program

2 Introduction

In recent years, sedentary habits have gained recognition as significant contributors to weight gain, overall mortality, and various chronic ailments such as cancer, cardiovascular issues, and diabetes. Among these sedentary behaviors, screen activity, referring to the time spent in front of electronic screens, stands out prominently in many populations, aside from occupational requirements. [1] However, people's behavior can be constrained by external environments or regulations. Based on background, the objective of this study is to investigate both compliance and effect of intervention program via the environmental modification approach on behavioral changes of mobile device use activities through an experiment among college students. The intervention programs include Intervention Program A and Intervention Program B. The intervention program A refers to a target allowance of 200 minutes for the total screen time per day and program B sets a target allowance of 50 pickups for the total pickups per day. For compliance, 1 coded for success and 0 coded for failure. We proposed two hypotheses: The first hypothesis is the intervention program would reduce the number of pickups per day. The second hypothesis is course credits would have an impact on the total number of compliance days.

3 Data Description

3.1 Data background

The study population is drawn from the entire class and includes data from 34 students. The collected data comprises mobile phone usage records from all classmates from January 1, 2024, to April 2, 2024 and baseline covariates. The data file contains two sheets.

The first sheet is screen time. It includes daily total screen time, daily total social screen time, number of pickups, the first time to pick up mobile after getting up and compliance. The second sheet contains baseline covariates such as pets, age, siblings, apps and so on. It describes the basic information of entire classmates. The raw dataset of screen time also includes Proportion.ST and Duration.per.use. In order to perform data preprocessing more easily, we deleted these two variables and generated these two variables using R lately. In the data sheet of baseline covariates, we deleted two variables, namely team and BMI, as they are irrelevant to the subsequent data modeling process. Therefore, the dimension of final screentime dataset is 2712×9 and the dimension of final baseline covariates dataset is 34×14.

3.2 Predictors of interest

We are primarily interested in two topics. The first topic is relationship between compliance and course credits. The second topic is relationship between the number of pickups and intervention program. Therefore, in the first model, we chose course credits as our main covariate and we also added sex, the number of workmate, the number of apps, procrastination score and average value into our model. The average value refers to the mean of daily total screen time during the three weeks preceding the intervention stage. In the second model, we chose treatment as our main covariate. Besides, we also add sex, the number of workmates, course credits, the number of apps, procrastination score, if weekdays or weekends, the number of pickups lagged by one period and the number of pickups lagged by two period into the model. As shown in the results, in the first model, course credits, the number of apps, procrastination score and average value are significant and have an impact on compliance. In the second model, All of the covariates are shown to be significant, implying that they affect the number of pickups.

3.3 Primary outcome of interest

We are primarily interested in two main outcomes. The first outcome is compliance. The compliance records whether the daily goals were successfully achieved. 1 coded for success and 0 coded for failure. The second main outcome is the number of pickups. We use the number of pickups to represent mobile screen activity use and to investigate whether the intervention program would reduce mobile screen activity.

3.4 Description of study cohort

Treatment	workmate	academic	non-academic	pets	sex	age	course credit	degree	job	siblings	apps	devices	procrastination score
A	0.94	0.76	1.53	0.06	76%male 24%female	23.71	12.88	35%previous have us degree 65%not	18%have job 82%not	0.94	3.65	2.82	35.29
B	1	1.06	1.29	0.06	65%male 35%female	22.94	13.59	35%previous have us degree 65%not	29%have job 71%not	0.41	3.94	2.94	37.41
ALL	0.97	0.91	1.41	0.06	71%male 29%female	23.32	13.24	35%previous have us degree 65%not	23%have job 77%not	0.68	3.79	2.88	36.35

Table 1: List of Baseline Covariates

The Table 1 describes the basic information of baseline covariates. For treatment A, the mean of workmate is 0.94, the mean of workmate of treatment B is 1. It shows the number of workmate in treatment A is less than treatment B. From the value of academic talk and non-academic talk, we can know that students are prefer to talk non-academic matters with their workmates. For the number of pets, students who in treatment A and in treatment B has the same mean of pets, with a value of 0.06. For sex, the proportion of males in treatment A is greater in number compared to the proportion of males in treatment B. For age, the average age in treatment A is 23.71, which is greater than the average age in treatment B of 22.94. For course credit, the average course credit in treatment B is 13.59, which is greater than the average age in treatment A of 12.88. The proportion of having job in treatment A is larger than treatment B. For siblings, the number of having siblings in treatment A is greater than treatment B. For students in treatment B, they prefer to use more apps and devices. For students in treatment B, they also have a higher procrastination score, with a value of 37.41.

4 Data Preprocessing

4.1 Missing data imputation

Missing data are a potential source of bias, especially when the number of missing values is substantial. To eliminate the potential bias of fitting model, we need to first fill in the missing values. The means of imputation is a principled paradigm widely adopted in practice to deal with missing values in data analyses.[3] Therefore, in this project, we adopted *MICE* package in *R* to impute the missing values when dealing with the screen time data. The default imputation method is **mean**. We have standardized the data collection period from January 1st to April 2nd. For some students, we removed excessive data, while for those missing certain data, we filled it in to complete it. When dealing with missing values in baseline covariates, we filled missing values in intervention program A with the mode of treatment A and filled missing values in intervention program B with the mode of treatment B. Finally, we obtained the complete dataset to fit the model.

4.2 Data cleaning

To fit these two models, we also should clean the complete dataset, including normalizing the data format, removing irrelevant data and adding relevant variables. Firstly, we standardized the date format, and then calculated the values of the variables Proportion.ST and Duration.per.use. The Proportion.ST is defined as the ratio of daily total social screen time over daily total screen time and the Duration.per.use is defined as the ratio of daily total screen time over daily total of pickups. Then we converted daily total screen time and daily total social screen time into minutes and deleted these two variables because we just use Total.ST.min and Social.ST.min to fit the model. Then, because we previously imputed the missing values for compliance, filling in all missing values, but the intervention program ran from March 27 to April 2, we removed the predicted data without in this time range in order to achieve a better model fit. Finally, we deleted data of some students because they only provides the data of few days and too much data is missing. Filling data with mean of imputation is meaningless and would lead to bias.

5 Data Analysis

5.1 Descriptive statistics

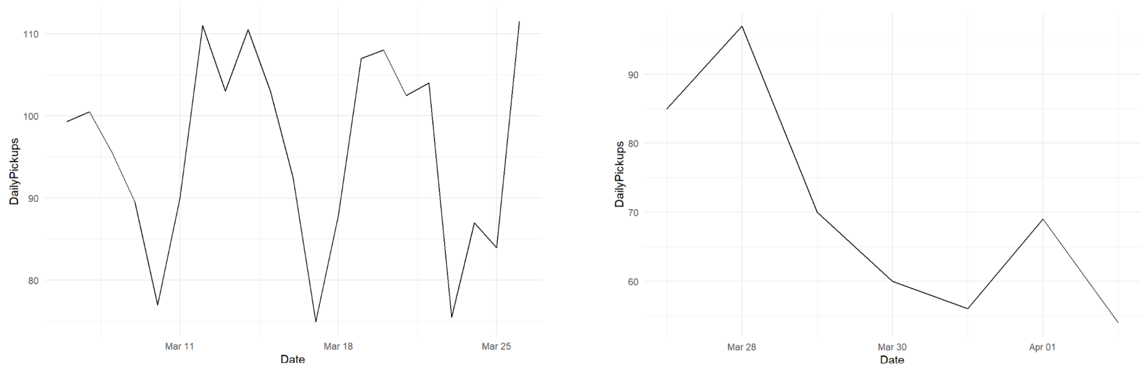
As shown in Table 2, we can know the procrastination score has the largest mean, which is 36.35. The pets has the smallest mean, which is 0.06. It means most of students do not have pets. Similarly, procrastination score has the largest standard deviation value and pets has the smallest standard deviation value. It means for procrastination score, the data points deviate more from their mean value than pets. Based on the value of skew, we can know the pets has the largest skew, with a value of 3.59. It shows a significant right-skewed distribution.The course credit has the smallest skew, with a value of -2.33. A negative value indicates a left-skewed tendency for this variable, but its large magnitude suggests a considerable degree of skewness in the distribution. The age has the largest kurtosis, with a value of 11.34. It indicates that the tails of the data distribution are taller than those of a normal distribution. It suggests the data contains more outliers or more concentrated in the tails. The country degree has the smallest kurtosis, with a value of -1.70. It indicates that the tails of the data distribution are flatter than those of a normal distribution. It suggests the data contains fewer outliers. The procrastination score has the largest standard error, with a value of 1.91. It indicates the difference between the sample mean procrastination score and the population mean procrastination score is approximately 1.91. The petes has the smallest standard error, with a value of 0.04. It shows the difference between the sample mean of pets and the population mean of pets is approximately 0.04.

Covariates	mean	SD	median	min	max	range	skew	kurtosis	SE
workmate	0.97	1.00	1.0	0	3	1	0.59	-0.90	0.17
academic talk	0.91	0.90	1.0	0	3	1	0.65	-0.52	0.15
non academic	1.41	1.73	1.0	0	8	3	1.98	4.52	0.30
pets	0.06	0.24	0.0	0	1	8	3.59	11.19	0.04
sex	0.71	0.46	1.0	0	1	1	-0.86	-1.29	0.08
age	23.32	1.65	23.0	21	31	1	2.97	11.34	0.28
course credit	13.24	3.08	13.0	0	17.5	10	-2.33	7.68	0.53
country degree	0.35	0.49	0.0	0	1	17.5	0.59	-1.70	0.08
job	0.24	0.43	0.0	0	1	1	1.19	-0.59	0.07
siblings	0.68	1.63	0.0	0	7	7	2.80	7.22	0.28
apps	3.79	1.84	3.0	1	10	9	1.17	1.79	0.32
devices	2.88	0.98	3.0	1	5	4	0.04	-0.10	0.17
procrastination score	36.35	11.13	37.0	16	58	42	0.04	-0.79	1.91

Table 2: Data description of baseline covariates

5.2 Data visualization

Figure 1 depicts the time series data of the number of pickups during the intervention and pre-intervention stages. As shown in Figure 1, the median of daily number of pickups of oscillates between 75 to 110 times per day and have a periodical trend in each week in baseline period. For each week, the number of daily pickups increased firstly and then decreased. In the treatment period, the median of pickups has a decrease trend and oscillate between 55 to 100 times per day.



(a) baseline number of pickups (b) treatment number of pickups

Figure 1: Time Series plots for number of pickups in two periods

As shown in Figure 2, we made a histogram for each of the number of total success and the mean course credit of each group. we can find that with the increase of average course credits in the treatment period, the total success of compliance decrease , which means the course credits have a negative effect on the compliance.

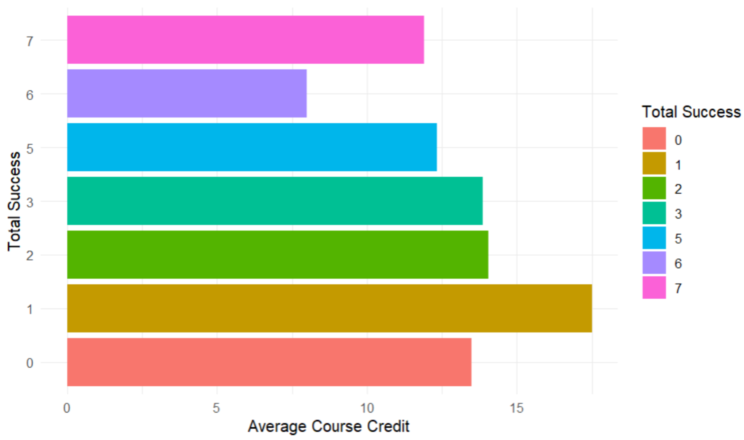


Figure 2: Average course credits by total compliance

6 Data modeling

This study employed two distinct statistical modeling approaches to investigate the effect of course credit on compliance behavior and the effect of intervention on number of pick-ups. We utilized generalized linear models with appropriate link functions and error distributions tailored to the nature of our dependent variables.

The variables included in the two models were:

- **course_credit**: A numeric variable indicating Course credit hours in the winter semester.
- **sex**: A categorical variable representing the gender of the participant. (female =0, male =1)
- **workmate**: A numeric count of the number of team members participants have ever worked previously for any other group projects before. (0,1,2)
- **apps**: A numeric count of the number of social apps installed on participants' major mobile devices that they use regularly for communication and engaging in virtual social activities. (e.g., 0,1,2,...)
- **procrastination_score**: The self-reported procrastination score assessed online based on 10 questions.
- **avg_value**: A normalized continuous variable representing an average value of Total Screen Time 3 weeks before the intervention began.
- **Weekday_Weekend**: A categorical variable distinguishing between weekday and weekend. (weekend = 1, weekday = 0)
- **treat**: A treatment indicator variable (e.g., the introduction of an intervention).
- **Pickups**: A numeric count of the number of pick-ups in days.
- **Total.ST.min**: A continuous variable representing the total screen time (in minutes) in days.

6.1 Analysis of Compliance Behavior

The first model was to explore the effect of course credit on compliance behavior (Total number of days of compliance) over the intervention period. We defined compliance in terms of successful adherence to a prescribed behavior as a proportion of total opportunities for compliance. Thus, the dependent variable was binomial, representing the number of successes and failures in compliance. This model allowed us to estimate the odds ratios for the likelihood of compliance associated with each predictor, holding other factors constant.

The data for the first model merges the baseline dataset and the last week's data from the screen activity dataset. Therefore, the merged dataset has 7 rows (days) of data for each individual.

This proposed model is

$$\begin{aligned}\log\left(\frac{p}{1-p}\right) = {} & \beta_0 + \beta_1 \text{ course\_credit} + \beta_2 \text{ sex} + \\ & \beta_3 \text{ workmate} + \beta_4 \text{ apps} + \beta_5 \text{ procrastination\_score} + \\ & \beta_6 \text{ avg\_value} \end{aligned} \tag{1}$$

, where p is the probability of compliance

6.2 Analysis of Number of Pick-ups

The second model was to explore the effect of intervention (A or B) on the number of Pick-ups per day. Since the number of Pick-ups is a count number, we deploy the log function as the link function, assuming Y follows Poisson distribution. This model allowed us to estimate the log of the number of pick-ups associated with the intervention (0 for pre-intervention period, 1 for intervention period), holding other factors constant.

The data for the second model merges the baseline dataset and the last four week's data from the screen activity dataset. Therefore, the merged dataset has 28 rows (days) of data for each individual. For the first 3 weeks, the value of variable 'treat' is 0, indicating intervention has not been deployed. For the last week, the value of variable 'treat' is 1, indicating intervention has been deployed.

For this particular model, we examined the autocorrelation within the number of pick-ups (figure 7 (a)). Based on the result, we decided to add lag(Pickups, 1) and lag(Pickups, 2) as our adjustment for they are highly significant in predicting the number of pick-ups. Since the Total Screen Time for each individual varies within a wide interval, we incorporated an offset term on log(Total.ST.min) to adjust the model's estimation to account for difference in exposure time (Total.ST.min). This ensured that the comparison between units is on a consistent basis.

In addition, since log(0) will lead to infinite, we replace Total.ST.min = 0 with Total.ST.min = 1.

This proposed model is

$$
\begin{aligned}
\log(\text{Pickups}) = \beta_0 &+ \beta_1 \text{ lag(Pickups, 1)} + \beta_2 \text{ lag(Pickups, 2)} + \beta_3 \text{ treat}+ \\
&\beta_4 \text{ sex} + \beta_5 \text{ workmate} + \beta_6 \text{ course\_credit}+ \\
&\beta_7 \text{ apps} + \beta_8 \text{ procrastination\_score} + \beta_9 \text{ Weekday\_Weekend} \\
&\text{offset} = \log(\text{Total.ST.min})
\end{aligned} \tag{2}
$$

7 Model diagnostic

7.1 Diagnostic for the first model

7.1.1 Residual diagnostic

In the residuals vs. fitted values plot (figure 7 (b)), residuals are spread around the zero line evenly without any discernible pattern, suggesting that the linear predictor is capturing the relationship well.

7.1.2 Q-Q plot and influential points

The Q-Q plot (figure 7 (c)) shows that most points follow the reference line closely, with slight deviations at the tails, particularly at the upper end. The overall trend suggests that the residual distribution does not violate the assumptions of normality too much.

Based on the outlier and leverage diagnostics plot (figure 7 (d)), the majority of data points are classified as normal. However, several points exceed both outlier threshold and leverage threshold, which should be classified as influential point. These points may represent data entry errors, unique cases, or variations not accounted for in the model. These should be furthur investigated to determine if they represent valid data points.

7.2 Diagnostic for the second model

7.2.1 Residual diagnostic

Based on the figure where residuals are plotted against fitted values for a Poisson generalized linear model (figure 8 (a)), the residuals are not evenly scattered. The relationship between the independent variables (log(pickups)) and the dependent variable may not be purely linear, or the model is missing important predictors or interaction terms that capture the underlying pattern of the data.

7.2.2 Dispersion test

Based on the equation $D = \sum_{i=1}^{n} r_i^2/df$. The dispersion statistic is 39.1, which is much bigger than 1. Therefore, overdispersion is present in the model. The assumption of Poisson distribution does not hold.

7.2.3 Q-Q plot and influential points

The Q-Q plot (figure 8 (b)) for our model shows points lying close to the reference line in the middle quantiles, but some deviation at the tails is evident. This deviation could indicate that the residuals have heavier tails than the normal distribution, suggesting the presence of outliers or that the normality assumption may not hold perfectly

Based on the outlier and leverage diagnostics plot (figure 8 (c)), the majority of data points are classified as normal. However, several points exceed both outlier threshold and leverage threshold, which should be classified as influential point.

8 Conclusion and Discussion

8.1 Results

Table 3: Logistic Regression Model Predicting Compliance

Variable	Estimate	Std. Error	z value	$\Pr(>\lvert z\rvert)$
Intercept	0.77563	1.03048	0.753	0.45164
Course Credit	-0.20513	0.06813	-3.011	0.00260**
Sex	-0.47165	0.33993	-1.388	0.16529
Workmate	-0.06610	0.16869	-0.392	0.69518
Apps	0.19868	0.08940	2.222	0.02626*
Procrastination Score	0.03183	0.01588	2.005	0.04498*
Average Value	-0.59567	0.18491	-3.221	0.00128**

The course credit (p = 0.00260) and average value (p = 0.00128) were found to be significant predictors of compliance, with their coefficients suggesting respective decreases in the log-odds of daily compliance. In contrast, the number of apps (p = 0.02626) was positively associated with compliance, indicating that an increased app usage is related to better compliance rate.

Based on the result, for our main predictor course credit, $\exp(\beta_{\text{course\_credit}}) = 0.8145$, This indicates that the estimated odds ratio of compliance for a one-unit increase in course credit is 0.8145.

Coefficient	Estimate	Std. Error	z value	Pr(>—z—)
(Intercept)	-2.425×10^{0}	2.822×10^{-2}	-85.938	$< 2 \times 10^{-16}$ ***
lag(Pickups, 1)	2.949×10^{-3}	8.927×10^{-5}	33.028	$< 2 \times 10^{-16}$ ***
lag(Pickups, 2)	1.480×10^{-3}	9.596×10^{-5}	15.425	$< 2 \times 10^{-16}$ ***
treat	-4.502×10^{-2}	8.083×10^{-3}	-4.957	7.17×10^{-7} ***
sex	1.162×10^{-1}	8.532×10^{-3}	13.622	$< 2 \times 10^{-16}$ ***
workmate	-3.058×10^{-2}	4.275×10^{-3}	-7.154	8.41×10^{-13} ***
course_credit	4.412×10^{-2}	1.940×10^{-3}	22.735	$< 2 \times 10^{-16}$ ***
apps	-3.698×10^{-2}	2.229×10^{-3}	-16.590	$< 2 \times 10^{-16}$ ***
procrastination_score	1.675×10^{-3}	4.048×10^{-4}	4.137	3.52×10^{-5} ***
Weekday_Weekend	-2.084×10^{-1}	8.714×10^{-3}	-23.912	$< 2 \times 10^{-16}$ ***

Table 4: Summary of model coefficients

Based on the result, the expected count of Pickups is multiplied by approximately 95.5% comparing intervention period to pre-intervention period, holding all other covariates constant. This suggests intervention (A or B) does have a positive effect on reducing the number of pick-ups, but only by a small amount.

8.2 Evaluation and future works for two models

For the first model, due to the relatively small sample size, the power to detect subtle deviations from model assumptions may be compromised. For future work, additional data collection is warranted. A larger dataset would provide more robust estimates.

Outlier and leverage diagnostics indicated the presence of influential data points. For future work, one can exclude those influential points and compare the two results.

For the second model, the residuals indicate potential non-linearity or omitted variable bias, suggesting that additional predictor variables or alternative functional forms may be necessary to improve the model fit.

The high over-dispersion score indicates Poisson distribution is not a good fit. The assumption for Poisson distribution does not hold for this dataset. For future work, one may compare observed relationship between mean and variance to expected relationship. Based on the comparison result, quasi-poisson or negative binomial distribution can be tested on the dataset.

9 Acknowledgement

Wenfei Mao:	Data cleaning, Missing value imputation, Report writing
Hong Cao:	Data Visualization, Data cleaning, Report Writing, Literature search, Debug.
Jingchao Yang:	Data processing, Model building/analysis, Model diagnostics, Conclusion, Report writing, General debugging.

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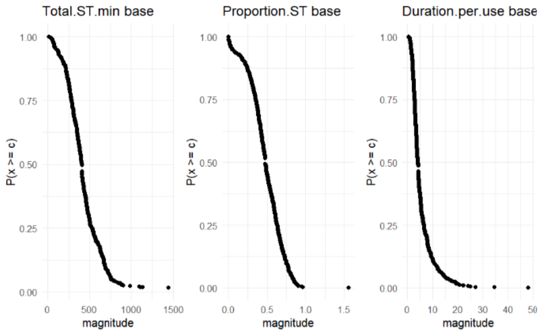
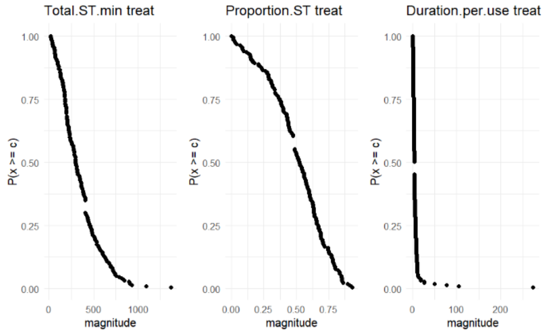
[2] Friedrich R R, Polet J P, Schuch I, et al. Effect of intervention programs in schools to reduce screen time: a meta-analysis[J]. Jornal de Pediatria (Versão Em Português), 2014, 90(3): 232-241.

[3] Austin P C, White I R, Lee D S, et al. Missing data in clinical research: a tutorial on multiple imputation[J]. Canadian Journal of Cardiology, 2021, 37(9): 1322-1331.

Appendix

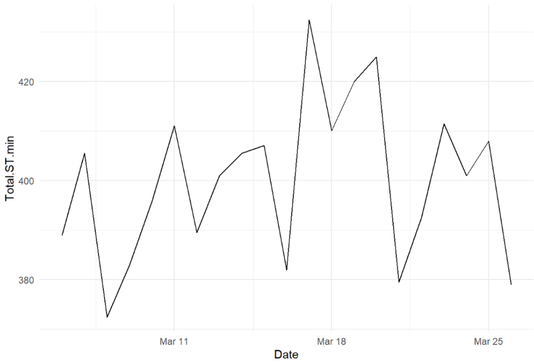


(a) occupation curve for baseline

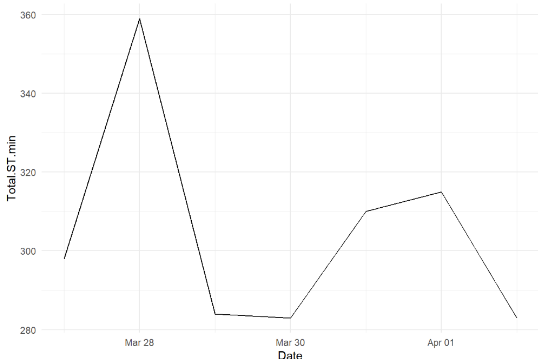


(b) occupation curve for treatment

Figure 3: Occupation Time Curves for two periods

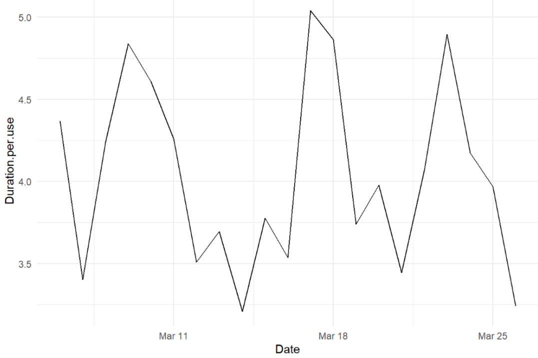


(a) baseline total screen time

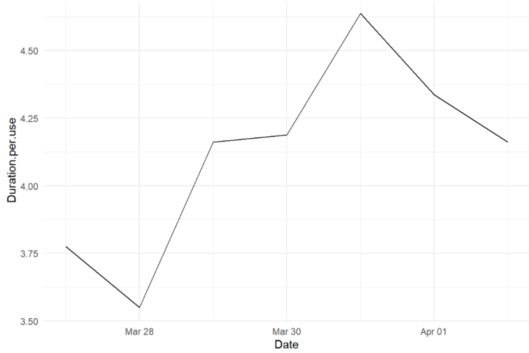


(b) treatment total screen time

Figure 4: Time Series plots for total screen time in 2 period

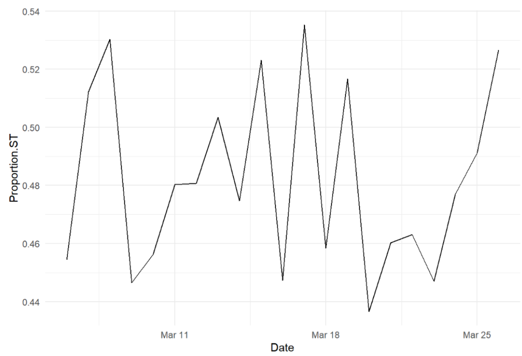


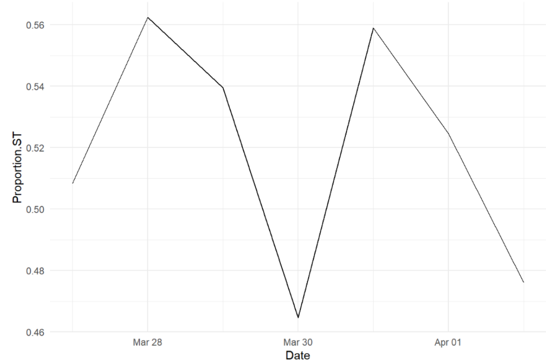
(a) baseline duration per use



(b) treatment duration per use

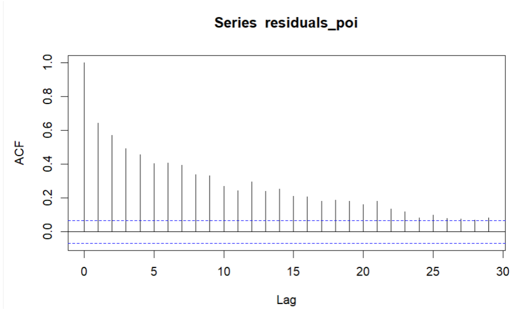
Figure 5: Time Series plots for duration per use in 2 period



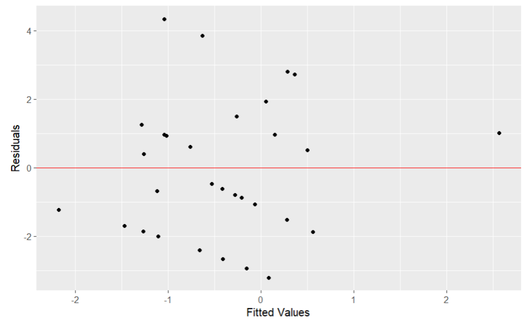


(a) baseline proportion of social screen time (b) treatment proportion of social screen time

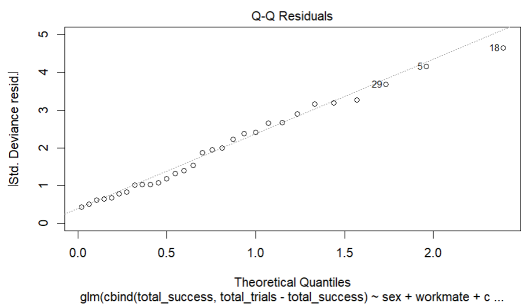
Figure 6: Time Series plots for proportion of social screen time in 2 period



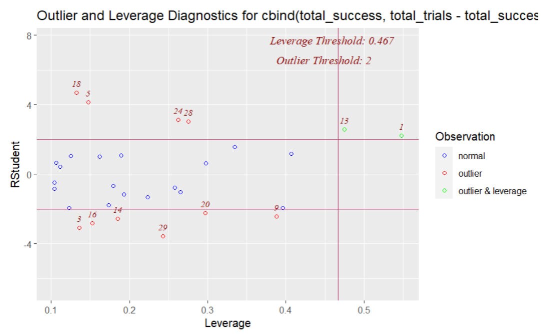
(a)



(b)

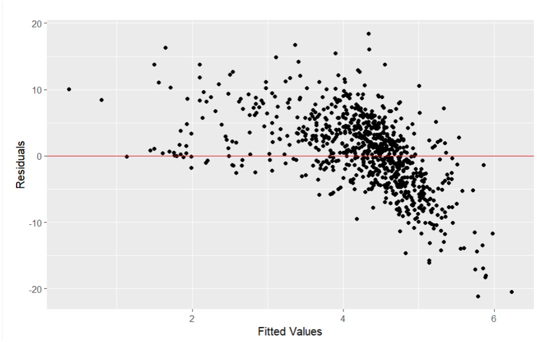


(c)

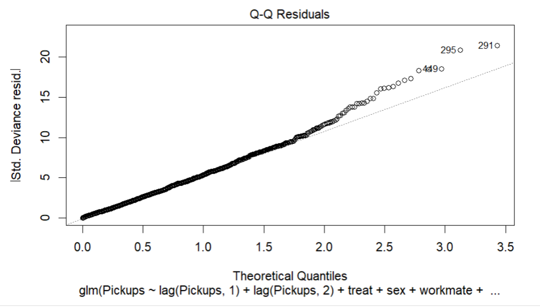


(d)

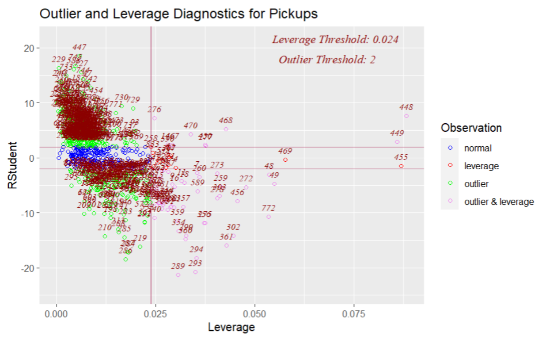
Figure 7



(a)



(b)



(c)

Figure 8

Github link: https://github.com/nxdlll/04W04-project2-code