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

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Introduction

Objective The objective is to investigate whether course credits would impact the success rate of compliance and whether intervention programs would reduce the number of pickups per day.

Hypotheses The hypotheses are intervention program would not reduce the number of pickups per day and course credits would not have an impact on the total number of compliance days.

Data Modeling In the first model, we chose course credits as our main covariate and we also added sex, the number of workmates, the number of apps, procrastination score, and average value into our model and we chose compliance as our response variable. 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, weekdays or weekends, pickups lagged by one period and lagged by two periods into the model, and choose pickups as our response variable.

Result Based on results, the p-value of course credits is 0.00260 and the p-value of treatment is 7.17×10^{-7}. It shows they are statistically significant. Therefore, our hypotheses are rejected.

Data Description

- **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.
- **Predictors of interest** 1. The first model: course credits(main covaraite), sex, workmate, apps, procrastination score, average value 2. The second model: treatment(main covariate), sex, workmates, course credits, apps, procrastination score, Weekday_Weekend, pickups, lag(Pickups, 1), lag(Pickups, 2)
- **Primary outcome of interest** Compliance and the number of pickups

Data Preprocessing

- **Misssing Data Imputation**
- adopted *MICE* package in *R* to impute the missing values when dealing with the screen time data. The default imputation method is **mean**.
- We removed excessive data and filled missing values to make sure the the time range is from January 1st to April 2nd.
- In baseline covariates sheet, 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
- **Data Cleaning**
- Standardized the date format and calculated the values of the variables Proportion.ST and Duration.per.use.
- Converted daily total screen time and daily total social screen time into minutes and deleted these two variables.
- Removed predicted data of compliance that falls outside the time range from January 1st to April 2nd deleted data of some students because they have too many missing data.
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Data Visualization

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. In the treatment period, the median of pickups has a decrease trend and oscillate between 55 to 100 times per day.

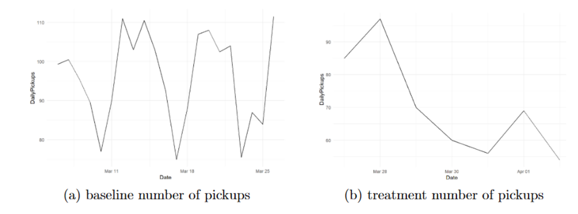


Figure 1. Time Series plots for number of pickups in two periods

With the increase of average course credits in the treatment period, the total success of compliance decreases.

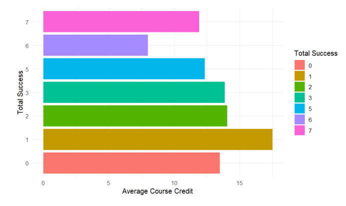


Figure 2. Average course credits by total compliance

Analysis of Compliance Behavior

The first model was to explore the effect of course credit on compliance behavior 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.

The data for the first model merges the baseline dataset and the last week's data from the screen activity dataset.

This proposed model is

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

, where p is the probability of compliance

Analysis of Number of Pickups

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 intervention (treat:0,1).

The data for the second model merges the baseline dataset and the last four week's data from the screen activity dataset. For the first 3 weeks, the value of variable 'treat' is 0 and for the last week, the value of variable 'treat' is 1.

This proposed model is

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

For this particular model, we examined the autocorrelation within the number of pick-ups. Based on the result, we decided to add lag(Pickups, 1) and lag(Pickups, 2) as our adjustment. 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 the difference in exposure time (Total.ST.min). In addition, we replaced Total.ST.min = 0 with 1 to avoid infinity.

Results

For the first model

Variable	Estimate	Std. Error	z value	Pr(> |z|)
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**

Table 1. Logistic Regression Model Predicting Compliance (First model)

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.

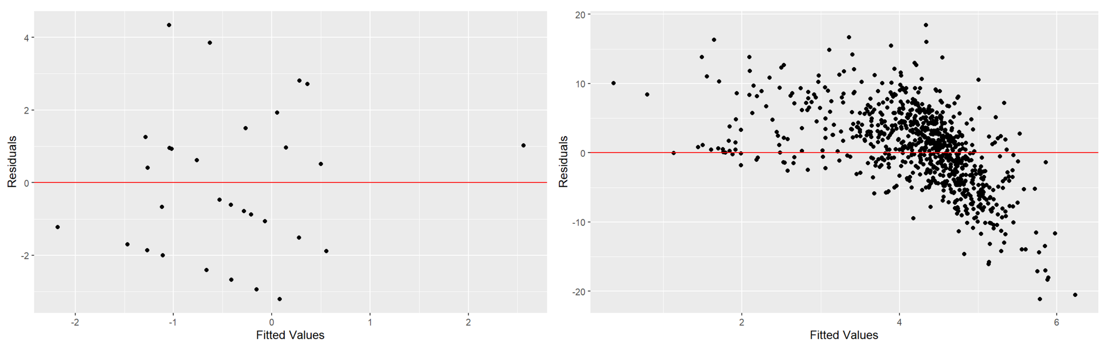
For the second model

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	-2.084×10^{-1}	8.714×10^{-3}	-23.912	$< 2 \times 10^{-16}$ ***

Table 2. Poisson Regression Model Predicting number of Pick-ups (Second model)

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.

The residual plots for the two models:



(a) Residual plots for model 1 (b) Residual plots for model 2

Figure 3. Combined Residual Plots

Conclusion

- **First Model**
  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.
- **Second Model**
  Intervention (A or B) does have a positive effect on reducing the number of pick-ups, but only by a small amount.

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