Investigating the effects of total screen time limits and phone pickups limits on reducing daily phone usage

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Abstract

Background: We collected data from the entire class of BIOSTAT 620 of 35 individuals of their screen time usage in winter semester under the randomized experiment with the intervention of environmental modification conducted in March, 2023.

Method: We use the multiple imputation (mice function in MI package) to generate the full data. Then, we detect the outliers of our two major outcomes by boxplot with range = 3 and delete abnormal points. LMM with random intercept and random intervention effect was used for total screen time intervention, GLMM with random intercept and random intervention effect was used for pickup intervention. Sandwich estimator was used to produce standard errors.

Results: The total screen time intervention was statistically significant (β=89.79, 95%CI: (36.36, 143.23), p = 0.001) on reducing daily screen time. The pickups intervention was also statistically significant (β=1.34, 95%CI: (1.11, 1.61), p = 0.002) on reducing phone pickups.

Conclusion: Both intervention plans showed statistically significant results in reducing the daily phone usage. These interventions might have benefits in studying school policy making on phone usage or some internal psychological elements in the future.

Key Phases: phone usage; multiple imputation; longitudinal data analysis; LMM; GLMM

Introduction

There is an increasing concern with the impact using social media on young people[1], and since mobile devices become easily addictive, we are interested in finding a way to reduce the possible addictive use of electrical products. In this study, we plan to test an intervention strategy of environmental modification, which attempts to change the user's physical environment or context to hopefully alter mobile device behavior. Essentially, the strategy sets a limit on the accessibility to a mobile device. By setting limits of accessibility, the environment is modified to encourage responsible and mindful use of technology and discourage excessive or addictive behavior. This strategy is often used in digital wellness programs or in parenting to help children and adults develop healthy habits and reduce the negative effects of excessive screen time on physical and mental health, social relationships, and productivity.

Our primary objective of this project is to investigate both compliance and effect of intervention programs via the environmental modification approach on behavioral changes of mobile device use activities through an experiment among college students. To analyze the effect, we carry out a 7-day intervention to reduce addiction of mobile device use. Specifically, this study includes two interventions of environmental modification, which are treatment A that sets a target allowance of 200 minutes for the total screen time per day, and treatment B that sets a target allowance of 50 pickups for the total pickups per day.

Our hypothesis for this project is that both the intervention plans will have a significant effect in reducing the daily phone usage. Thus, we are especially interested in two variables, total screen time and pickups, and our aim is to compare the intervention effect on the total screen time limit and pick limit.

We collected data from the entire class of BIOSTAT 620 of 35 individuals of their screen time usage in winter semester in 2023 under the randomized experiment with the intervention of environmental modification conducted in March, 2023, where 18 individuals are given treatment A and 17 individuals are given treatment B. Our study is significant because we are trying to improve our understanding of behavioral patterns on the use of electronic devices among college students who are at high risk for adverse health outcomes due to excessive use of mobile devices.

Data description

This dataset was collected from an entire class of graduate students and it contains information from 33 individuals, with 20 variables, including ID, sex, pickups, treatment, etc.

(Initially, there are 35 participants, but we choose to remove two subjects with IDs 19 and 23 that have excessive missing values of the baseline variables.) Thus, our analysis is based on 18 individuals given treatment A and 15 individuals given treatment B. These data were collected from December 18, 2022 to March 26, 2023.

We don't have a large number of graduate students as subjects, and all the subjects in our study are from bio-statistic or relevant departments, thus, the results might lead to potential bias. What's more, missing data exists, which is a limitation of our study. Also, we collected the first pickup time and used it to represent the wakeup time, however, we noticed that some subjects' first pickup time is around midnight, which cannot be viewed as the first pick up time, and that might lead to bias.

Table 1 (including Table.1.1, Table.1.2 and Table.1.3) shown below lists summary descriptive statistics for all collected variables.

Table. 1.1 *Variable Interpretations*

Variable Name	Interpretation
Total.ST.min	Daily entries of total screen time in minutes
Social.ST.min	Daily entries of total social screen time in minutes
Pickups	Total number of the times the user picked up the phone
Pickup.1st	the time of the first pickup
Treatment	Intervention treatment type (sets a target allowance of 200 minutes for the total screen time per day = A, sets a target allowance of 50 pickups for the total pickups per day = B)
Workmate	Number of team members you have ever worked previously for any other group projects before (0, 1, 2)
Academic	Number of team members you talk to regularly about academic matters (course notes, homework, exam, application for PHD, intern/ job application etc).
Non.Academic	Number of team members you have ever talked to about topics other than academic matters (0, 1, 2). Examples of such topics include movie, concert, video game, sport, food, travel etc.
Pets	Live with pets at home that you look after (yes = 1, no = 0)
Sex	Female = 0, male = 1
Age	In year
Coursehour	Course credit hours in the winter semester
Degree	Country where previous degree received (US = 1, Non-US = 0)
Job	Currently have a job (> 10 hours/ weeks) such as RA/ TA/ Others (yes = 1, no = 0)
Siblings	Number of siblings
Apps	Number of social apps installed on your major mobile device that you use regularly for communication and engaging virtual social activities
Devices	Number of personal mobile devices processed such as cell phone, iPad, iWatch
Procrastination	The self-reported procrastination score assessed online based on 10 questions

Table. 1.2 *Variables for Screen Time and Number of Pickups*

Variable Name	Total (N = 2913)	A (N = 1576)	B (N = 1337)
Total.ST.min			
Mean (Std)	371.501 (178.205)	383.756 (179.147)	356.749 (176.007)
Missing	132 (4.5%)	57 (3.6%)	75 (5.6%)
Social.ST.min			
Mean (Std)	134.093 (105.030)	120.742 (89.392)	149.760 (118.968)
Missing	170 (5.8%)	95 (6.0%)	75 (5.6%)
Pickups			
Mean (Std)	96.297 (60.442)	94.088 (59.176)	98.862 (61.802)
Missing	56 (1.9%)	41 (2.6%)	15 (1.1%)

Table.1.3 *Baseline Variables*

Variable Name	Total (N = 35)	A (N = 18)	B (N = 17)
Workmate			
Mean (std)	1.065 (0.964)	1.176 (1.015)	0.929 (0.917)
Missing	4 (11.4%)	1 (5.6%)	3 (17.6%)
Academic			
Mean (Std)	1.645 (1.142)	1.588 (1.417)	1.714 (0.726)
Missing	4 (11.4%)	1 (5.6%)	3 (17.6%)
Non.Academic			
Mean (Std)	1.516 (0.996)	1.471 (1.068)	1.571 (0.938)
Missing	4 (11.4%)	1 (5.6%)	3 (17.6%)
Pets			
Yes	6 (17.1%)	1 (5.6%)	5 (29.4%)
No	27 (77.2%)	17 (94.4%)	10 (58.8%)
Missing	2 (5.7%)	0 (0%)	2 (11.8%)
Sex			
Male	13 (37.1%)	5 (27.8%)	8 (47.1%)
Female	21 (60%)	13 (72.2%)	8 (47.1%)
Missing	1 (2.9%)	0 (0%)	1 (5.8%)
Age			
Mean (Std)	23.303 (1.828)	23.056 (1.305)	23.600 (2.324)
Missing	2 (5.7%)	0 (0%)	2 (11.8%)
Coursehour			
Mean (Std)	13.438 (1.435)	13.611 (1.471)	13.214 (1.410)
Missing	3 (8.6%)	0 (0%)	3 (17.6%)
Degree			
USA	23	10	13
Non - USA	9	8	1
Missing	3 (8.6%)	0 (0%)	3 (17.6%)
Job			
Yes	9 (25.7%)	4 (22.2%)	5 (29.4%)
No	23 (65.7%)	14 (77.8%)	9 (52.9%)
Missing	3 (8.6%)	0 (0%)	3 (17.5%)
Siblings			
Mean (Std)	0.576 (0.708)	0.389 (0.608)	0.800 (0.775)
Missing	2 (5.7%)	0 (0%)	2 (11.8%)
Apps			
Mean (Std)	3.844 (2.316)	3.611 (2.429)	4.142 (2.214)
Missing	3 (8.6%)	0 (0%)	3 (17.6%)
Devices			
Mean (Std)	2.031 (1.031)	1.777 (0.732)	2.357 (1.277)
Missing	3 (8.6%)	0 (0%)	3 (17.6%)
Procrastination			
Mean (Std)	35.394 (12.316)	38.778 (13.086)	31.333 (10.314)
Missing	2 (5.7%)	0 (0%)	2 (11.8%)

Data imputation

We removed two subjects with IDs 19 and 23 that have excessive missing values of the baseline variables. We use the R mice package which provides multiple imputation(replacement values) for multivariate missing data. And we didn't change the default number of the imputed dataset which is equal to 5 (m = 5) . The method is based on Fully Conditional Specification, where each variable is imputed by a separate model with all the other variables. We call the MI function mice.

We assessed the efficiency of multiple imputation. For baseline data, we considered procrastination as the outcome because according to the pickups model, procrastination is significantly associated with the pickups which we consider as one of the final outcomes. The relative (variance) efficiency (RE) of an imputation represents how well the true population parameters are estimated which is related to both the amount of missing information as well as the number (m) of imputations performed. For another dataset which includes the total screen time and pickups, we considered the total screen time and pickups as outcome separately because they are our intervention and we will analyze them later. According to the table.X, we can find that three RE is high enough, thus our imputation performed well.

Table.2 *the efficiency of multiple imputation*

	λ	RE
the efficiency of multiple imputation for baseline data (outcome = procrastination)	0.9946	0.8341
the efficiency of multiple imputation for screen data (outcome = Total.ST.min)	1.0000	0.8333
the efficiency of multiple imputation for screen data (outcome = Pickups)	0.9993	0.8334

Data preprocessing

We combine two datasets into one dataset. For full data, we consider the pickups and total screen time as outcomes to test the efficiency of interventions.

We create the boxplot with a long whisker(range = 3). According to the Figure.X below, we can find that the number of outliers of total screen time is 2 and the number of outliers of Pickups is 4.

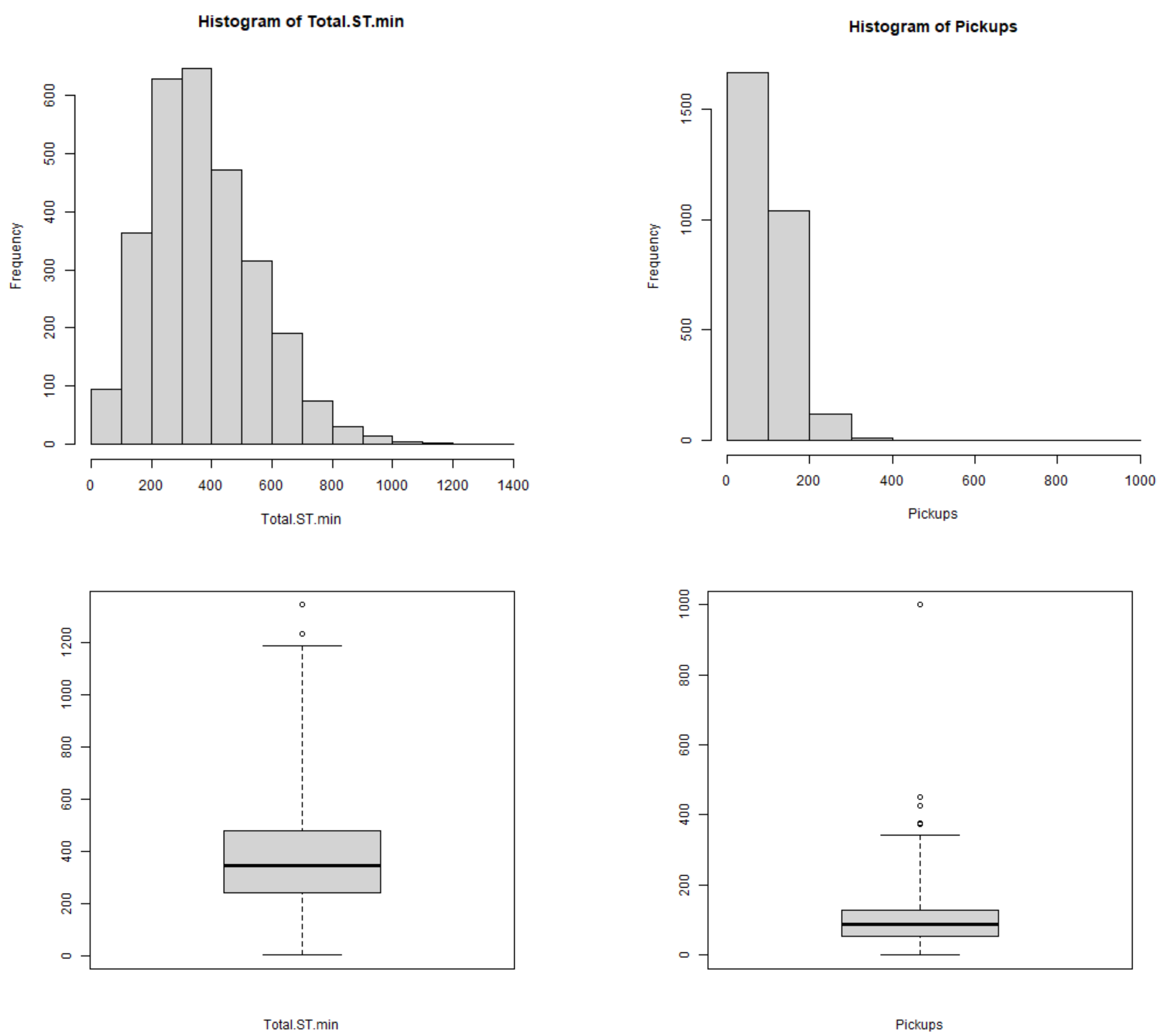

Figure.1 *the outliers of outcomes*

We deleted the outlier which deviated the most (pickups = 1000, row = 1955) which is shown below. As the result of Figure.X, obviously, 1000 pickups is abnormal compared to other pickups of 25-th subject.

Table.3 *the information of abnormal point*

ID	Date	Total.ST.min	Social.ST.min	Pickups	Pickup.1st	Treatment	Workmate	Academic	Non.Academic
25		281	146	1000	0.3833	P	2	2	2

Pets	Sex	Age	Coursehour	Degree	Job	Siblings	Apps	Devices	Procrastination
0	1	24	16	1	0	0	6	5	19

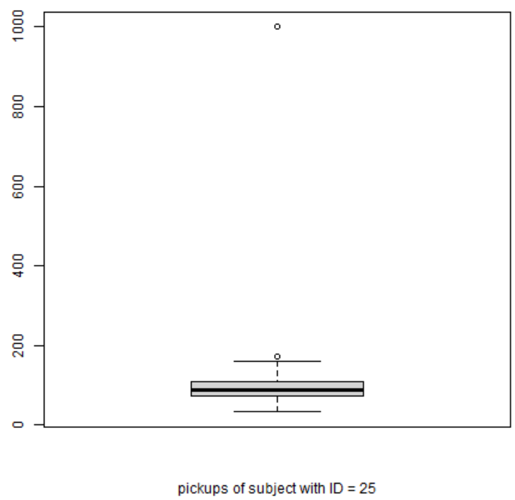

Figure.2 *the boxplot of pickups of subject with ID = 25*

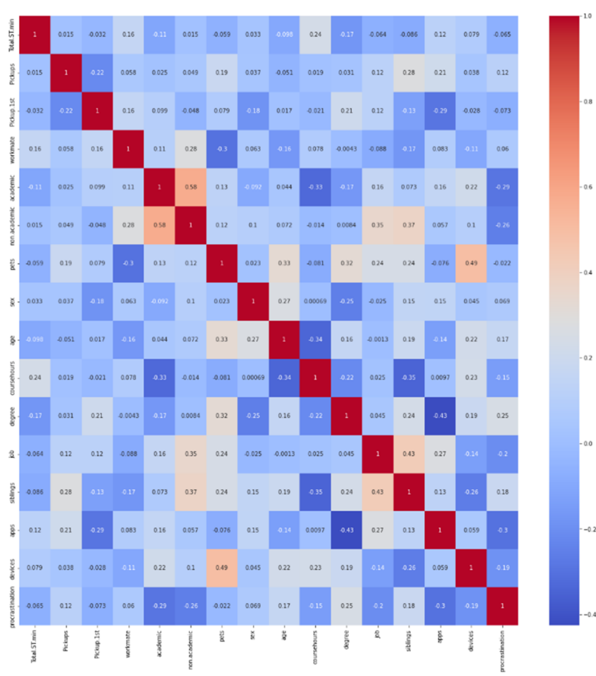

Figure.3 *Correlation Coefficient Matrix*

From the correlation coefficient matrix we found that some variables are comparatively highly correlated, such as non-academic and academic have a correlation coefficient of 0.58, which indicates if people have talked about academic topics with each other, they might also talk about non academic topics. Surprisingly, Total screen time and number of pickups have a correlation coefficient of 0.015, which indicates very little correlation. This is reasonable, for example, some people may use their phone to watch dramas, so that they will not pick up the phone often while watching.

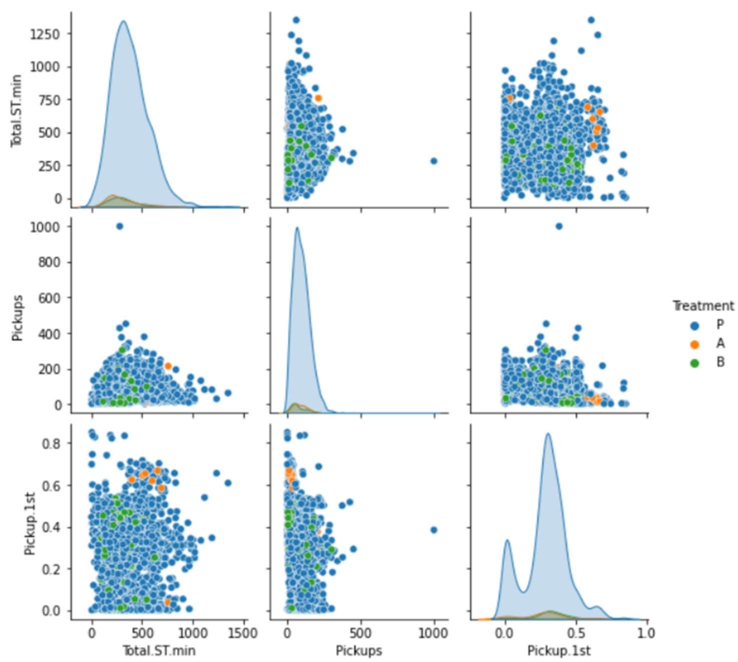

Figure.*4 Pair plots for Total Screen time and Pickups*

The above plot shows variable distributions (available on the diagonal). We found that given treatment A (sets a target allowance of 200 minutes for the total screen time per day) and B (sets a target allowance of 50 pickups for the total pickups per day), total screen time and number of pickups will decrease, and treatment A will lead to more decrease of total screen time usage, while treatment B leads to more decrease of number of pickups. However, treatment A and B do not have much influence on affecting the first pickup time.

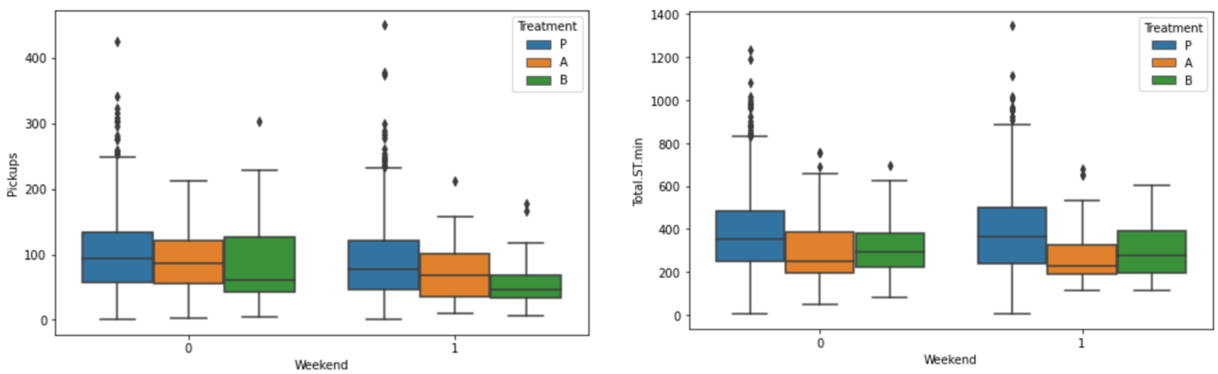

***Figure.5** Boxplots for Pickups and Total Screen Time Exploring Treatment Effects*

We separate the data into weekends and weekdays and make boxplots. We found that the number of pickups varies more during weekends given treatment B from the above plot, while total screen time varies more during weekdays given treatment A.

Data analysis

Method

Since the data is repeated-measured/longitudinal, methods including GEE GLM, LMM, and GLMM are considered. Since our aim is to compare the intervention effect on the total screen time limit and pickups limit, two different models (total screen time as outcome, pickups as outcome) were built respectively. The coding for the treatment group is treating the treatment group as the baseline for all models.

We included all baseline variables into all models. For total screen time intervention, the outcome is total screen time and the predictors include treatment, date, pickups, number of workmates that had worked together before, number of workmates that had talked to on academic matters, number of workmates that had talked to on non-academic matters, if living with a pet, gender, credit hours this semester, currently have a job or not, number of siblings, number of social apps installed, number of personal mobile devices, and self-reported procrastination score. For pickup intervention, the outcome is pickups and the predictors are all the same except that total screen time was added and pickups was removed.

For the total screen time intervention, we fitted two Normal regression models with GEE assuming exchangeable correlation and AR-1 respectively. We then fitted a LMM model with a random intercept and a random slope on intervention (total screen time intervention). For pickup intervention, we fitted two Poisson GLM models with GEE assuming exchangeable correlation and AR-1 as well. We then fitted a GLMM model assuming Poisson distribution with a random intercept and a random slope on intervention (pickups intervention). For the GEE GLM models used in both interventions, QIC values between two correlation matrix assumptions were used to select the final model. Although it is intuitive to assume an AR-7 correlation structure since similar patterns should occur between calendar days with a weekly interval, errors occurred during model fitting (R and Python) and unsupported correlation structure (SAS) limited our further investigation. The final models we chose were the LMM and GLMM models for two intervention plans respectively. R^2 was used to compare the goodness of fit of the fitted models. The LMM model diagnosis was done by investigating the normal Q-Q plots and the distribution of residuals. The GLMM model diagnosis was done by investigating the Poisson Q-Q plot and the deviance residual. Sandwich estimator was used to calculate standard errors and furtherly produce p-values to account for potential heteroscedasticity and/or correlation in the errors.

Result

For total screen time intervention, the QICs of exchangeable correlation and AR-1 GEE GLM model is 3408 vs 3479. Therefore, the AR-1 correlation structure was selected for its smaller QIC. The corresponding result of this model showed that the intervention effect was statistically significant ($\beta = 74.83$, 95%CI: (20.23, 129.43), $p = 0.007 < 0.05$).

The LMM model with random intercept and random intervention effect term showed that the main effect of intervention was also statistically significant ($\beta = 89.79$, 95%CI: (36.36, 143.23), $p = 0.001$). Therefore, the estimated main effect of total screen time intervention is reducing an average of 89.79 minutes on daily total screen time adjusting for other covariates.

The R^2 for this model is 40.97%, which indicates that the predictors explained a relatively large amount of variances.

For pickup intervention, the QICs of exchangeable correlation and AR-1 GEE GLM model is -63029 vs -63822. Therefore, the AR-1 correlation structure was selected for its smaller QIC. The corresponding result of this model showed that the intervention effect was not statistically significant ($\beta = 0.13$, 95%CI: (-0.09,0.31), $p = 0.15 > 0.05$) for reducing pickups.

The GLMM model with random intercept and random intervention effect term showed that the main effect of intervention was also statistically significant ($e^{\beta} = 1.34$, 95%CI: (1.11, 1.61), $p = 0.002$). Therefore, the estimated main effect of pickup intervention is reducing an average of 1.34 on daily pickups adjusting for other covariates conditional on the individual's latent characteristics.

The R^2 for this model is 99.99%, which indicates that the predictors explained a large amount of variances.

Table 4. *Results for the intervention effect*

	Intervention Effect Estimate	95%CI	p-value
Total screen time limit (LMM)	89.79	(36.36, 143.23)	0.001
Pickups limit (GLMM)	1.34	(1.11, 1.61)	0.002

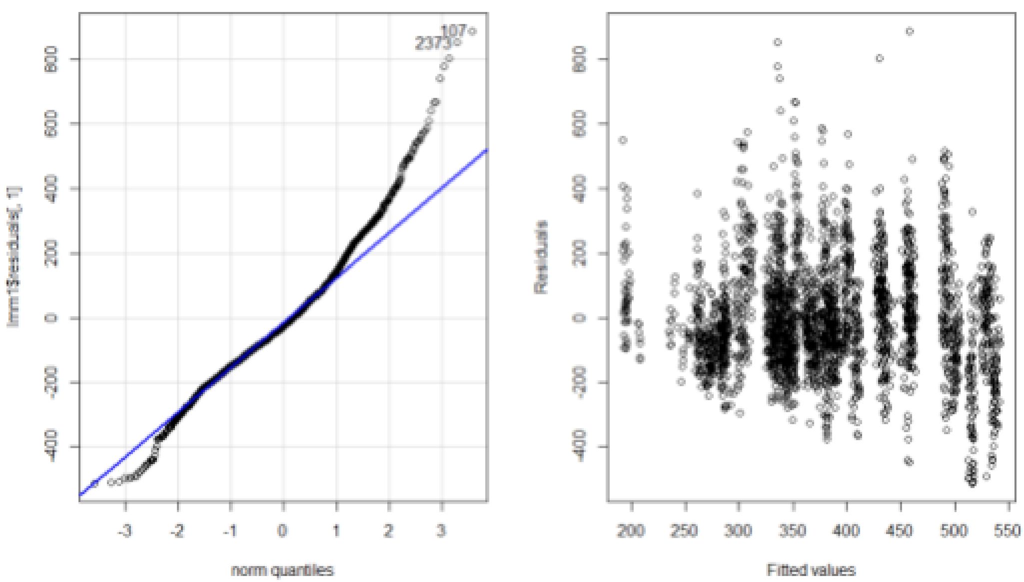

Figure 6. *Q-Q plot and residual plot for total screen time limit intervention (LMM)*

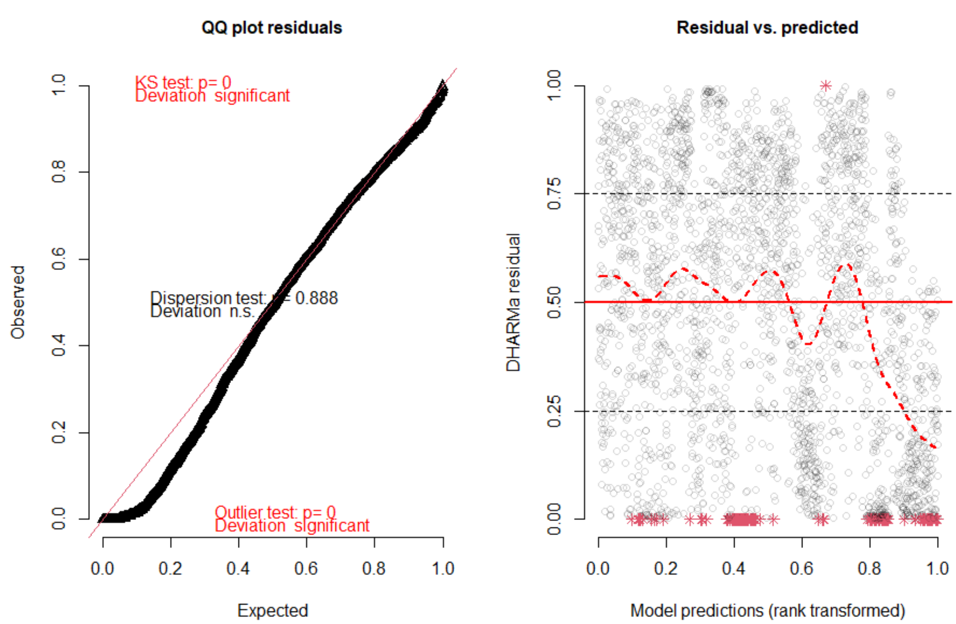

Figure 7. *Q-Q plot and residual plot for pickups limit intervention (GLMM)*

Discussion

For the pickups intervention AR-1 correlation structure GEE model, the p value for treatment effect is 0.15 > 0.05 which is quite different from the GLMM result ($p = 0.002$) and the exchangeable correlation GEE model ($p = 0.010$). Although the AR-1 structure did have a smaller QIC value compared with the exchangeable correlation model, it might still not be the right choice.

For GLMM model, the residual plot showed that there are a lot of outliers on the lower tail and the residual plot showed a lot of outliers around 0 as well (the DHARMa package uses a transformation called the inverse cumulative distribution function (ICDF) to map the simulated residuals onto (0, 1)). Although this certainly violated our assumption, but since most of the outliers are on the lower tail, which indicates that we might only have underestimated our treatment effect but not overestimated, plus we have adopted sandwich estimator and the sample size is fairly large, this issue might not strongly affect our confidence in our GLMM model.

For the LMM model, the residual plot showed that most of the residuals are densely clustered around 0, but there heavy tails are still observed on both tails from the Q-Q plot. This can be observed from residual plots either, but obviously more outliers gather around the upper tail. Since our coding is setting the intervention group as baseline (0 for intervention, 1 for non-intervention), this only indicates the intervention effect might only be underestimated rather than overestimated. Similarly, the usage of sandwich estimator plus the large sample size would support our confidence in this model.

However, since the R^2 for the LMM model is much lower compared to the GLMM model, although this might not be comparable, it may still suggest that the LMM model may still have some potential to get improved. For example, normal distribution might not be a good choice since the time variables are only recorded up to minute accuracy, therefore, all times are positive integers. Poisson distribution or other distribution might also be considered. Moreover, since we failed to adopt a GEE Normal GLM with AR-7 correlation structure, adding a lag-7 term of the total screen time might also be able to improve the model. Furtherly, since the data is time series data, an auto-regressive moving average (ARMA) or auto-regressive integrated moving average (ARIMA) model might also be a good choice if we build them for each person and finally compare the effect of treatment along with multiple testing corrections.

Conclusion

Both intervention plans showed statistically significant results in reducing the daily phone usage. Although this study was done among graduate students rather than for younger students that may not have this strong self-discipline, it can still provide educational value to school policy making. Psychological perspective might be further considered for its role-playing on making students use phones less by referring to this study.

Acknowledgement

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References

[1]Barthorpe A, Windstone L, Mars B, Moran P. Is social media screen time really associated with poor adolescent mental health? A time use diary study. J Affect Disord. 2020; 274: 864-870. doi: 10.1016/j.jad.2020.05.106