Assessing the Efficacy and Compliance of Intervention Strategies on Limiting Screen Time Usage

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GitHub Link: https://github.com/CAROLINeeeeDeng/VENTURE_project2

Key Phrases: Meta-Analysis, Linear Mixed Effect Model, Generalized Linear Regression

Abstract

Excessive screen time usage has been linked to numerous health issues, such as obesity and depression (Zhu et al., 2023). Intervention strategies to limit screen time usage are a potentially effective method to mitigate the negative side effects of screen time data. The goal of this study is to evaluate the effectiveness of two types of interventions in reducing screen time usage. A meta-analysis was used to summarize participant data, and generalized linear models (GLMs), as well as linear mixed models (LMMs), were used to explore inference. The implemented analytical techniques revealed a remarkable reduction in screen time among participants due to the interventions. Both environmental modification interventions—reducing daily screen time allowance and reducing number of pickups—significantly reduced screen time, with the former showing better performance in limiting screen time than the latter. Additionally, it was found that the previous day's screen time affected the screen time of the following day, while no other baseline or demographic data had a significant effect as such.

Introduction

The effects of excessive screen time on the physical and mental health of humans have been the source of many studies since the invention of screens and mobile devices. Greater duration of screen time usage has been found to be heavily associated with several different types of adverse health outcomes, such as depression, sleeping problems, and obesity-related complications (Zhu et al., 2023). Gaining a better understanding of the issues that arise from excessive screen time, as well as what other factors may contribute to these issues, is more important than ever with the prevalence of screens in everyday life. More insight into these potential causes could also better inform researchers on potential intervention strategies to reduce screen time, and thus mitigate potential health issues.

The objective of this research study is to address adverse health issues by evaluating the efficacy of applying different intervention strategies to reduce screen time. More specifically, the objective can be broken down into three parts: 1) determining if an intervention is better than no intervention; 2) determining if there is a difference in effect between interventions, and if so, identifying which intervention is better; and 3) evaluating compliance among users for their assigned interventions. It was hypothesized that incorporating some intervention will be more effective in reducing screen time than no intervention, as users are incentivized to achieve a defined goal (Jones et al., 2021). It was also hypothesized that there will be a difference in effectiveness between the interventions and that one will be better in reducing screen time when compared to the other.

These analyses can provide valuable insights: what/whether an intervention is ideal for reducing screen time, what external factors may play a role, and how well compliance is achieved among users. This will allow for tailoring and recommending future intervention strategies (based on analyzed results) to reduce screen time usage and mitigate its associated negative effects on human health most effectively.

Generalized linear models (GLMs) and linear mixed-effect models (LMMs) have been fitted for exploring inference, as GLMs allow for understanding the relationship between the covariates and the response variable by accommodating Poisson and binomial distributions. Meanwhile, LMMs provide insights into random effects within data, allowing for the analysis of complex data structures (including repeated measures), thereby capturing subject-specific variations. Furthermore, meta-analysis techniques have been implemented by summarizing data from each participant and calculating estimates for GLMs.

In this study, there were two different treatments (Intervention A and Intervention B) that were randomly assigned to users to determine the effectiveness of implementing environmental restrictions on limiting daily screen time. The first intervention (A) set a target allowance of 200 minutes for total screen time per day and the second intervention (B) set a target allowance of 50 for total pickups per day. Analyses were performed using this data in comparison to baseline data to evaluate the effectiveness of interventions and how well compliance was achieved (our stated objectives) in order to evaluate our hypotheses and recommend the most effective treatments for reducing daily screen time usage in the future.

Data Description

This study was performed using mobile device screen time data over the course of the Winter 2024 semester. Participants in the cohort were graduate students (34 total) at the University of Michigan enrolled in BIOSTAT 620, a course in the School of Public Health. At the start of the semester, users collected as much data as was available over the previous weeks using their device history.

Screen time was collected daily until April 2, 2024, with the intervention period spanning from March 27, 2024 until April 2 (total of 7 days). For the study, participants were randomly assigned a pseudo-ID (for identification) and an intervention, with the goal of reducing screen time through an environmental restriction. Intervention A set a target allowance of 200 minutes for total screen time per day and Intervention B set a target allowance of 50 total pickups per day. Users kept track of cumulative savings over the course of the intervention period, as well as compliance status (1 for success and 0 for failure). Along with the total screen time restriction, limiting pickups was selected as an intervention plan because pickups are known to be heavily correlated with total screen time (Shaw et al., 2020). Collected screen time data included the variables of total screen time (minutes), total social screen time (minutes), pickups, first pickup time, pseudo ID, phase, treatment (intervention), compliance, date, and weekday/weekend status (based on dates). In addition to screen time data, users also reported baseline covariates, including number of pets, sex, age, course credit hours, country of previous degree, job status, number of siblings, number of social apps, number of mobile devices, procrastination test score, and the number of team members worked with, talked to about academics, and talked to about non-academic matters. After data collection by individuals for both screen time usage and other relevant baseline covariates, data spreadsheets were submitted and aggregated to create a class-wide dataset for further analysis. Appendix 1 illustrates the complete study design and data collection procedure.

Based on class-wide data, a table with summary statistics for phase, compliance, treatment (intervention), sex, age, and total screen time in minutes was generated (Table 1).

Participants	**n = 34**
Treatment	
Treatment A	17
Compliance	49.6%
Treatment B	17
Compliance	25.8%
Sex	
Male	19
Female	10
NA/No Answer	5
Variables	**Mean(SD)**
Age (years)	23.3(1.84)
Total Screen Time (min)	405.7(217.06)
Pickups	97.1(47.88)

Table 1: Descriptive statistics of study cohort

The analysis is focused on determining the effect of intervention strategy on total screen time usage and whether one intervention is better than the other. Initial figures were generated to display detailed patterns for our variables of interest: number of pickups (offset), weekend/weekday status, lag-1 of total screen time in minutes, phase, and intervention groups. For all individual data (grouped by both phase and treatment during intervention), boxplots are shown in Appendices 2-4, pairwise scatterplots are shown in Appendices 5-6, time series plots are shown in Appendices 7-8, and autocorrelation function (ACF) plots are shown in Appendices 9-12. The boxplots show a greater screen time during baseline than during intervention, a greater screen time for Intervention B than Intervention A, and little difference in screen time between weekday/weekend status. Pairwise scatterplots show a strong correlation between screen time and lag-1 screen time for both phases, as well as for both treatments during intervention. Time series plots show a reduced mean screen time during intervention than baseline, and for Intervention A than Intervention B during the intervention period. ACF plots show many significant autocorrelations for mean screen time at low lag values for the baseline, but none during intervention. ACF plots also show a significant autocorrelation for a lag value of 1 for Treatment A during intervention, but there are no other significant autocorrelations present in either Treatment A or Treatment B during the intervention period.

Data Preprocessing

The study involved aggregated screen time data over the course of the Winter 2024 semester, until April 2, 2024. However, the task of processing the full dataset was challenging due to disparate date formats and inconsistent time intervals used by individual participants during data collection. Additionally, there were discrepancies in the handling of missing screen time data; some participants left blank rows to signify absent data, while others omitted such days entirely. Furthermore, there was a diverse representation of binary variables in the data.

Data Normalization and Transformation

The screen time and baseline covariate datasets were first merged by pseudo ID to create one large dataset. Afterward, the date formats were standardized across the dataset to ensure a uniform structure such that all dates were consistently represented, thus eliminating any ambiguity in temporal data. Binary variables presented a challenge due to their varied representation; some were indicated with terms such as "Success" or "Fail", "True" or "False", or numerical values of 0 and 1. Therefore, all binary variables were normalized to a consistent format, converting all textual representations to a 0 and 1 numeric format. The screen time data in minutes (from Total.ST and Social.ST) was recalculated to double check the values, and a new variable, 'weekday', was generated to denote a dummy variable that was set to 1 if day t was a weekday, and 0 if it was a weekend. Additionally, duplicate entries for the same pseudo ID were removed, ensuring a cleaner dataset for downstream analyses.

Missing Values Imputation

For the participant with pseudo ID 1329 in the dataset, the variables Total.ST.min and Social.ST.min exhibited missing data across several days. To maintain the continuity and integrity of Participant 1329's data for downstream analyses, the mice function in R was utilized to fill gaps in the dataset based on the 'Predictive Mean Matching' (PMM) method to impute missing values for these two variables. The PMM method can impute values that are not outliers, thus preserving the original distribution and integrity of the data. Implementing an imputation procedure using the mice function also reduces the risk of model overfitting, as it does not rely on stringent assumptions about data distributions.

Data Analysis

Intervention Effect

The initial analysis focused on the effectiveness of receiving versus not receiving an intervention. Meta-analysis techniques were first applied to assess the significance of the effectiveness of interventions A and B in regulating phone screen usage. The data was separated into two subsets, data_A and data_B, with each subset representing participants who received the corresponding intervention.

It was found that participants with pseudo IDs 2880, 6759, and 9285 did not provide any treatment data from March 27 to April 2. Also, participants with pseudo IDs 2520, 8622, and 9680 only provided treatment data without the baseline covariate data preceding March 27. This data cannot be imputed since the missing values are not random, and the integrity of treatment and baseline data is crucial. Since data from every individual is relevant and matters in this analysis, the data entries for these four participants from the dataset were temporarily removed.

The next examination performed was a meta-analysis of daily total screen time using the Poisson log-linear model. $Y_{i,t}$ is defined as the daily total screen time ('Total.ST.min') for user *i* on day t, corresponding to the intervention the participant received. A_t and B_t are dummy variables equal to 1 if an intervention was received on day *t*, and 0 otherwise (baseline). W_t is a dummy variable which is set to 1 for weekdays and 0 for weekends. Additionally, the daily number of pickups was added as an offset term in our models, as this covariate was known to have a direct effect on the total screen time (response). These covariates were selected to reduce confounding effects in our models. Two lag-1 transitional Poisson log-linear models were considered, as shown below:

$$\ln(\lambda_{i,t}) = \beta_0^A + \beta_1^A \ln(Y_{i,t-1}) + \beta_2^A A_t + \beta_3^A W_t$$

$$\ln(\lambda_{i,t}) = \beta_0^B + \beta_1^B \ln(Y_{i,t-1}) + \beta_2^B B_t + \beta_3^B W_t$$

According to the results of meta-estimates and corresponding standard errors (Tables 2-3), at a level of α=0.05, both interventions A and B have a significant influence on daily total screen time compared to no intervention, as both exhibited p-values less than 0.05.

Parameter	Meta.Estimate	Std.Error
beta_0	-0.84941851	0.027082709
beta_1	0.49082345	0.004416782
beta_2	-0.09294844	0.006783646
beta_3	-0.31744426	0.003343005

Table 2: Intervention Group A

Parameter	Meta.Estimate	Std.Error
beta_0	0.1995274	0.025999638
beta_1	0.2171155	0.004447490
beta_2	0.4639214	0.005018577
beta_3	-0.1316976	0.003009072

Table 3: Intervention Group B

Based on results from the previous analysis, demographics were also investigated to see if they had any effects. In addition to the three variables and offset term already considered, eight more covariates were selected from the baseline: participants' sex, age, number of pets, course credits for the winter semester, number of siblings, number of social apps, number of personal mobile devices, and procrastination test score. No data of individual users had to be removed because any observations with missing values for baseline covariates were automatically excluded from the models. A GLM for the overall data without distinguishing intervention groups was made, with a dummy variable $I_t = 1$ for receiving an intervention (either A or B) at day *t* and 0 for baseline:

$$\ln(\lambda_{i,t}) = \beta_0 + \beta_1 \ln(Y_{i,t-1}) + \beta_2 I_t + \beta_3 W_t + \beta_4 Pets_i + \beta_5 Sex_i + \beta_6 Age_i + \beta_7 CourseCredit_i + \beta_8 Siblings_i + \beta_9 Apps_i + \beta_{10} Devices_i + \beta_{11} Procastination_i$$

According to the Poisson regression model, it is evident that intervention plays a statistically significant role in influencing total screen time, given a p-value of essentially zero. However, contrary to what was expected, the positive coefficient suggests that it is associated with an increase in screen time. Furthermore, results show that all covariates involved have a significant influence on screen time usage (Table 4).

	Estimate	Std. Error	z value	$\Pr(>\|z\|)$
(Intercept)	-3.0671097	0.0378884	-80.95	<2e-16 ***
log(lag_TSM)	0.4931706	0.0028315	174.17	<2e-16 ***
Intervention	0.1211326	0.0046722	25.93	<2e-16 ***
weekday	-0.1932423	0.0025780	-74.96	<2e-16 ***
pets	-0.5032964	0.0065830	-76.45	<2e-16 ***
sex	-0.2141002	0.0026843	-79.76	<2e-16 ***
age	0.1229377	0.0013305	92.40	<2e-16 ***
course.credit	-0.0790504	0.0007760	-101.87	<2e-16 ***
siblings	-0.0901928	0.0011519	-78.30	<2e-16 ***
apps	0.0829474	0.0008001	103.67	<2e-16 ***
devices	-0.1294412	0.0014792	-87.51	<2e-16 ***
procrastination.score	0.0035188	0.0001297	27.12	<2e-16 ***

Table 4: Intervention GLM Estimates

While GLMs demonstrate that the intervention is a significant predictor of screen time, some considerations suggest a need for a more nuanced approach. The GLM assumes that observations are independent and identically distributed (ID), which may not account for natural clusters within the data, such as variations among individual participants. Considering the repeated measures across multiple days and the potential intra-individual correlations within our data, an LMM was used with pseudo IDs introduced as random effects. This allowed capturing within-subject variability, providing a more accurate estimate of the intervention's effects by considering the nonindependence of data points associated with each participant. The following formula was utilized in this analysis:

$$Y_{i,t} = \beta_0 + \beta_1 \ln(Y_{i,t-1}) + \beta_2 I_t + \beta_3 W_t + \beta_4 Pets_i + \beta_5 Sex_i + \beta_6 Age_i + \beta_7 CourseCredit_i + \beta_8 Siblings_i + \beta_9 Apps_i + \beta_{10} Devices_i + \beta_{11} Procastination_i + \gamma_{pseudo\_id}$$

Unlike findings from the GLM, where all predictors including the intervention were found to be significant, the LMM indicates that only the intervention and the log of the lag-1 of total screen time, with estimates of -66.9805 and 98.4302 and p-values less than α=0.05, are significantly associated with total screen time (Table 5). Thus, from this LMM analysis, it can be concluded that when controlling for the random effects of individual variability, an intervention has significant and negative associations with screen time (as expected), indicating its potential effectiveness in reducing mobile device usage when individual differences are considered.

	Estimate	Std. Error	df	t value	$Pr(>\|z\|)$
(Intercept)	-142.9377	401.7792	16.2546	-0.356	0.727
log(lag_TSM)	98.4302	6.1206	1961.1980	16.082	<2e-16 ***
Intervention	-66.9805	9.0884	1977.3489	-7.370	2.5e-13 ***
weekday	-7.5220	5.4504	1964.2806	-1.380	0.168
pets	-7.3327	96.9273	15.5369	-0.076	0.941
sex	-52.0780	40.5728	15.7459	-1.284	0.218
age	-3.6635	14.1980	15.8563	-0.258	0.800
course.credit	-0.1854	8.8652	15.9249	-0.021	0.984
siblings	-8.7273	13.5125	16.4701	-0.646	0.527
apps	13.6535	11.4954	15.6627	1.188	0.253
devices	-14.9424	19.4281	15.6622	-0.769	0.453
procrastination.score	1.8492	1.6516	16.4939	1.120	0.279

Table 5: Intervention Mixed Effects Estimates

Comparisons Between Interventions

After evaluating the effectiveness of receiving an intervention (either A or B), an LMM regression test using the 'lmerTest' package in R was run. The results of this test showed that in both intervention groups, the presence of an intervention strategy and the prior day's screen time were the most significant predictors of the current day's screen time ($p < 0.05$) (Table 6).

	Intervention A			Intervention B		
	Estimate	Std. Error	$\Pr(>\lvert z\rvert)$	Estimate	Std. Error	$\Pr(>\lvert z\rvert)$
(Intercept)	541.3705	935.5254	0.586	259.887	908.355	0.79294
log(lag_TSM)	104.9430	9.3665	<2e-16	81.874	8.097	<2e-16
Intervention	-105.9888	15.6645	2.5e-11	-38.699	10.644	0.00029
weekday	-13.8012	8.9204	0.122	-2.275	6.622	0.73124
pets	-17.0304	98.4541	0.86489	-13.305	106.239	0.90825
sex1.0	65.6207	73.7320	0.412	-126.497	661.543	0.13149
age	-34.3307	31.7923	0.326	-20.084	44.830	0.68429
course.credit	-7.9835	15.5149	0.628	-14.337	13.161	0.35507
siblings	7.8597	19.0691	0.696	-28.701	32.041	0.43617
apps	18.2995	16.4807	0.320	-10.814	23.462	0.67614
devices	6.4790	37.2803	0.869	-21.394	46.586	0.67741
procrastination.score	0.6859	2.9839	0.826	2.109	2.391	0.44196

Table 6: Combined Estimates from Mixed Effects Models

Furthermore, we wanted to compare the effectiveness of the two interventions more directly by including both in one model. Dummy variables A_t and B_t were introduced for the overall dataset, where A_t = 1 if Intervention A was received on day *t*, and 0 otherwise, and the same for B_t . A linear fixed model was then considered:

$$Y_{i,t} = \beta_0 + \beta_1 A_t + \beta_2 B_t + \beta_3 \ln(Y_{i,t-1}) + \beta_4 W_t + \beta_5 Pets_i + \beta_6 Sex_i + \beta_7 Age_i$$
$$+ \beta_8 CourseCredit_i + \beta_9 Siblings_i + \beta_{10} Apps_i + \beta_{11} Devices_i$$
$$+ \beta_{11} Procastination_i + \gamma_{pseudo\_id}$$

Based on the results (Table 6), we performed a Wald test with the following hypothesis:

$$H_0: \beta_1 = \beta_2, \qquad H_1: \beta_1 \neq \beta_2$$

$$W = \frac{(\hat{\beta}_1 - \hat{\beta}_2)^2}{\widehat{SE}\{\hat{\beta}_1\}^2 + \widehat{SE}\{\hat{\beta}_2\}^2} = 16.9765 > \chi^2_{(1),0.95} = 3.84$$

Therefore, we can reject the null hypothesis and conclude that there is a statistically significant difference in effectiveness between Intervention A and Intervention B, with A being significantly more effective in reducing screen time compared to B, as shown by the more negative coefficient for "TreatmentA" in the model output when compared to "TreatmentB" (-110.6308 vs -36.0231, respectively) (Table 7).

	Estimate	Std. Error	t value	Pr(> |z|)
(Intercept)	-122.4915	407.8418	-0.300	0.76770
TreatmentA	-110.6308	13.8203	-8.005	2.08e-15 ***
TreatmentB	-36.0231	11.6997	-3.079	0.00211 **
log(lag_TSM)	95.6524	6.1299	15.604	< 2e-16 ***
weekday	-7.6219	5.4272	-1.404	0.16036
pets	-17.0304	98.4541	-0.173	0.86489
sex1.0	-55.5765	41.2035	-1.349	0.19635
age	-3.2185	14.4151	-0.223	0.82616
course.credit	-0.7402	9.0012	-0.082	0.93548
siblings	-10.6638	13.7217	-0.777	0.44803
apps	14.0364	11.6726	1.203	0.24692
devices	-15.1741	19.7271	-0.769	0.45315
procrastination.score	1.8098	1.6762	1.080	0.29575

Table 7: Comparison Mixed Effect Estimates

Intervention Compliance

The compliance for the two interventions was another aspect of interest in the study. We examined the combined data from both interventions, focusing solely on treatment data. A dummy variable C_t was introduced to represent compliance with the intervention on day *t*, where C_t = 1 indicated compliance with either Intervention A or B, and C_t = 0 indicated non-compliance. Considering the random effects of individual variability, a generalized linear mixed model (GLMM) was fitted:

$$C_t = \beta_0 + \beta_1 \ln\left(Y_{i,t-1}\right) + \beta_2 W_t + \beta_3 Pets_i + \beta_4 Sex_i + \beta_5 Age_i + \beta_6 CourseCredit_i + \beta_7 Siblings_i + \beta_8 Apps_i + \beta_9 Devices_i + \beta_{10} Procastination_i + \gamma_{pseudo\_id}$$

According to the results presented in Table 8, it is observed that none of the variables have substantial statistical significance concerning compliance. The associated p-values are higher than the significance level of 0.05. This suggests that when individual variances due to the random effects of pseudo-identifiers are considered, the influence of the covariates' fixed effects on compliance does not reach statistical significance.

	Estimate	Std. Error	df	t value	Pr(> $|z|$)
(Intercept)	2.856790	1.825421	15.791294	1.565	0.137
log(lag_TSM)	-0.002520	0.060734	143.862808	-0.041	0.967
weekday	-0.057793	0.065342	151.756750	-0.884	0.378
pets	-0.121310	0.416627	12.934267	-0.291	0.776
sex1.0	0.056836	0.176450	12.895625	0.322	0.753
age	-0.031139	0.064540	15.384900	-0.482	0.636
course.credit	-0.067260	0.046953	13.544369	-1.433	0.175
siblings	-0.016955	0.086710	13.261023	-0.196	0.848
apps	0.017828	0.054159	13.422315	0.329	0.747
devices	0.098256	0.091471	13.984455	1.074	0.301
procrastination.score	-0.003925	0.007746	13.744561	-0.507	0.620

Table 8: Compliance Mixed Effect Estimates

Conclusions and Discussion

When incorporating baseline covariates, linear mixed models (LMMs) and generalized linear mixed models (GLMMs) generally give a more accurate picture of the relationships compared to generalized linear models (GLMs). This suitability stems from the presence of repeated measures from the same participants within the dataset, where not all observations are independent from each other. LMMs and GLMMs account for this by including random effects, which explain individual variability beyond the observed covariates, thus absorbing some of the variability that might otherwise be attributed to the fixed effects in a GLM.

Considering all models comprehensively, it can be concluded that receiving an intervention is significantly effective in reducing screen time on mobile phones when compared to receiving no intervention. Additionally, out of the two treatments, Intervention A (daily screen time allowance) was found to be more effective than Intervention B (daily pickup allowance) in reducing screen time usage, though both interventions still had a significant effect. Furthermore, there is no significant relationship between the collected baseline covariate data and compliance with the intervention. This suggests that the effectiveness of an intervention transcends individual baseline characteristics, reinforcing its broad applicability to numerous populations. Collectively, these insights provide a strong foundation for advocating intervention implementation to reduce screen time usage and conduct further studies in diverse settings.

We developed the following methods to explore the effectiveness of interventions in reducing screen time usage. Our methodology is advantageous in that we not only determined if an intervention was effective, but we also identified which intervention performed better and how well compliance was achieved. We also took random effects of individual variability into account in our models, allowing for the analysis of complex data structures (which can be applied to future studies), and capturing subject-specific variations.

Our experience with data analysis mostly went smoothly and we were able to achieve our project objectives and prove our hypotheses. We were interested and surprised by our results which showed that Intervention A had a significantly better performance in reducing screen time than Intervention B. Though we were initially surprised to see this large discrepancy, this result ultimately made sense because Intervention A was directly targeted at screen time reduction whereas Intervention B targeted it indirectly.

Limitations and Future Work

One limitation of this study was the heterogeneity and lack of standardization in the overall dataset. As mentioned previously, the preprocessing of this dataset presented substantial challenges due to disparate formats and representations. This lack of uniformity necessitated extensive manual intervention for data cleaning and standardization before performing further analyses. This not only impeded the efficiency of data processing but also could have introduced potential biases.

Future research would benefit from standardizing data recording formats before collection from individuals, which would streamline the data preprocessing phase, reduce the workload involved in data cleaning, and enhance the reliability of subsequent analyses. Future studies could also implement a longer intervention period so that intervention effects and effects on compliance can be better studied with larger sample sizes in the data.

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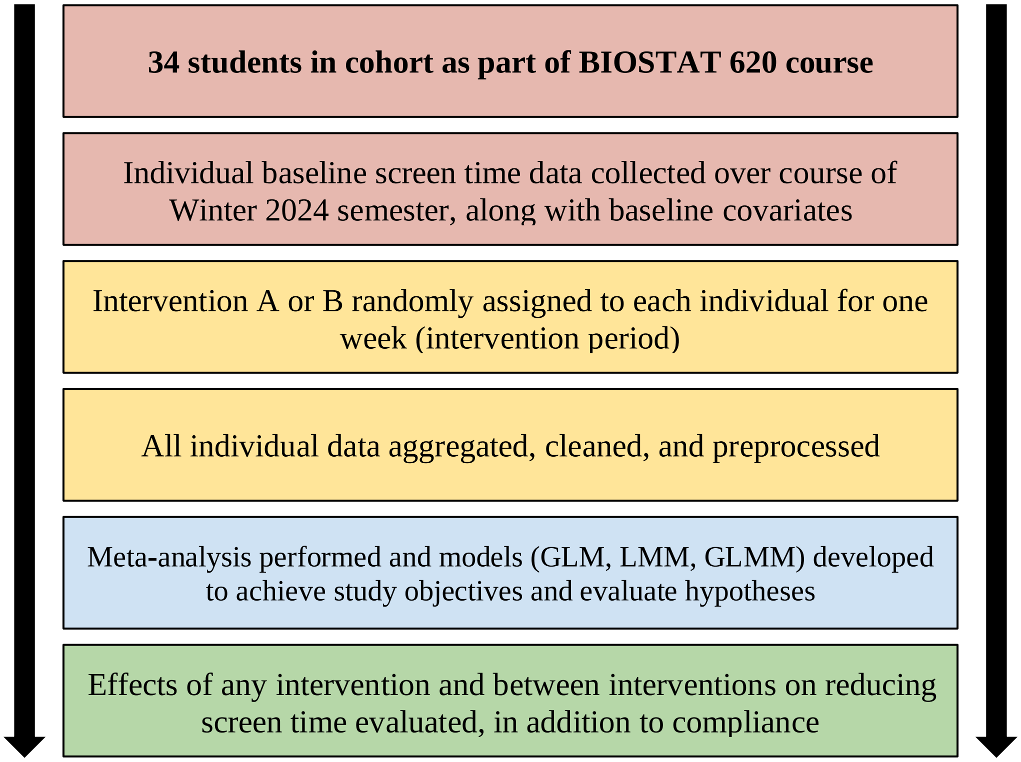
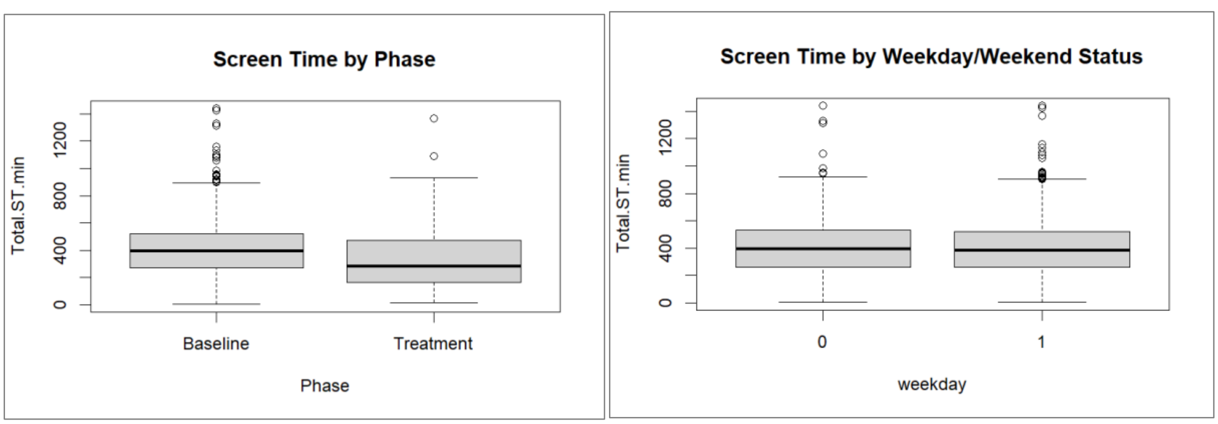
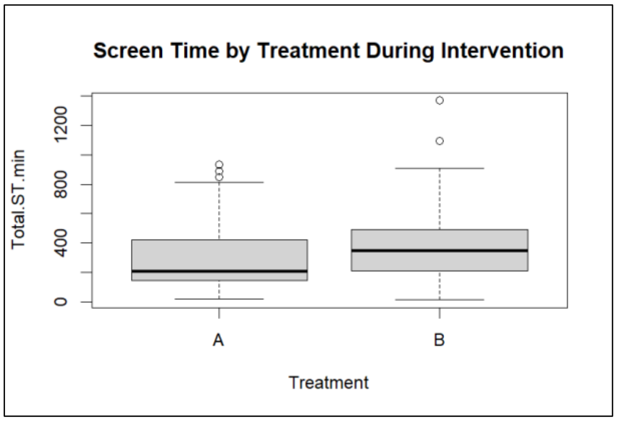
Appendix:

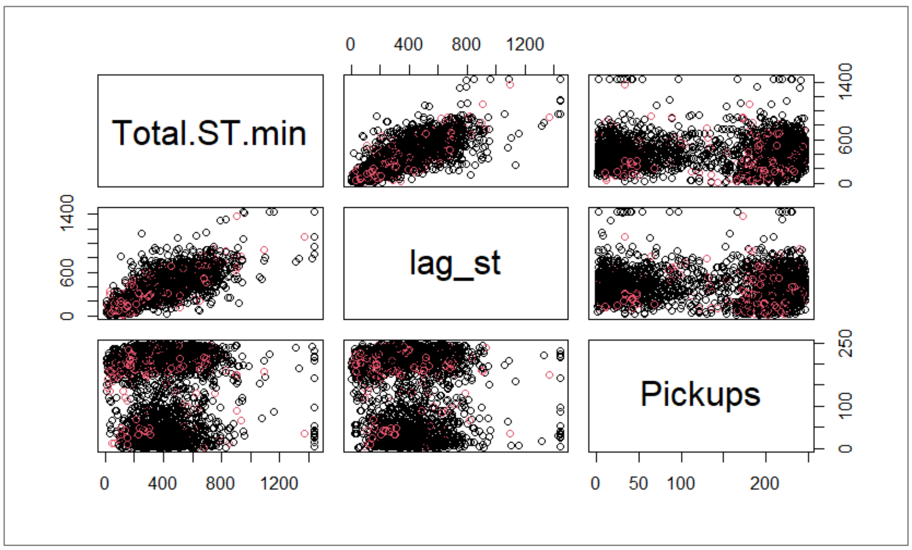


Appendix 1. Implemented Study Design and Workflow for Project Analyses.



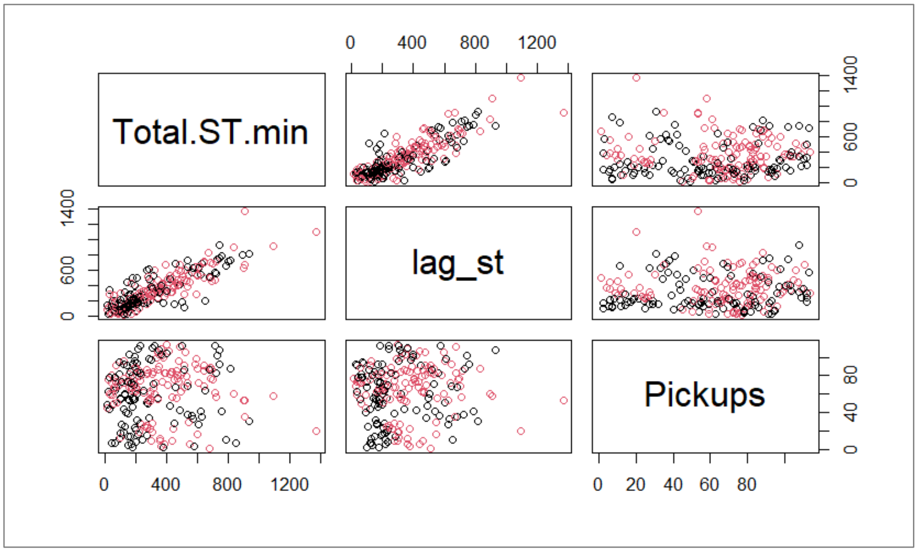


Appendices 2-4. Boxplots of Total Screen Time in Minutes by Selected Binary Variables.



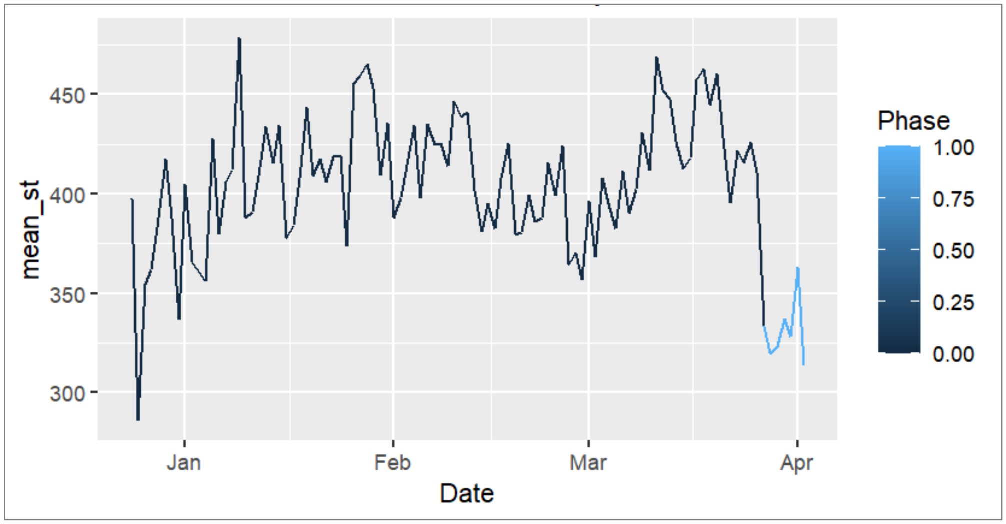
Appendix 5. Pairwise Scatterplot of Selected Variables by Phase.

Black = Baseline; Red = Treatment.



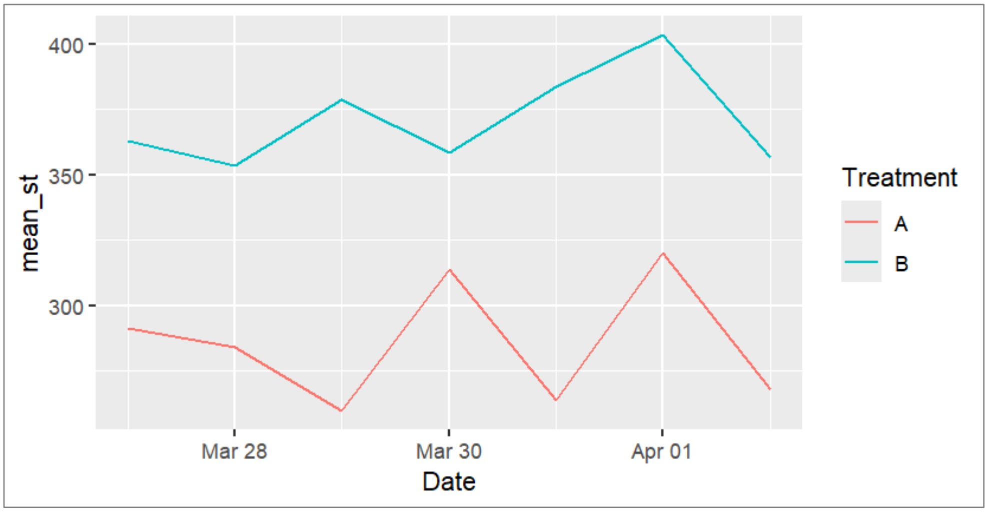
Appendix 6. Pairwise Scatterplot of Selected Variables by Treatment During Intervention.

Black = Treatment A; Red = Treatment B.



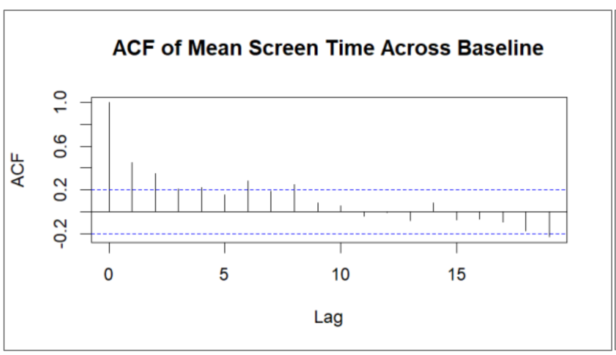
Appendix 7. Time Series Plot of Mean Screen Time by Phase.

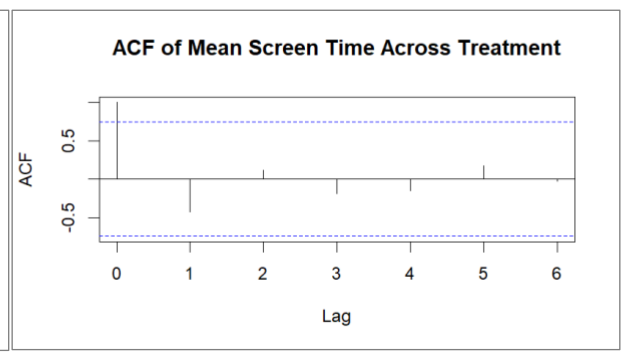
Dark Blue = Baseline; Light Blue = Intervention.



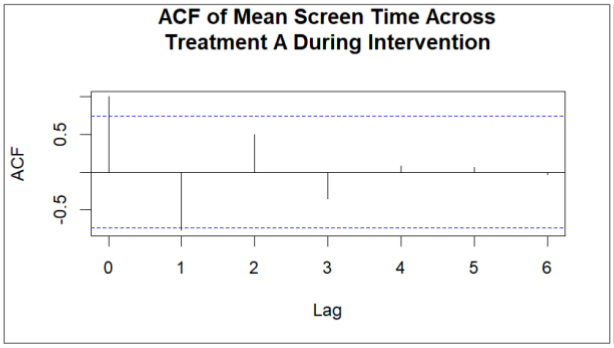
Appendix 8. Time Series Plot of Mean Screen Time by Treatment During Intervention.

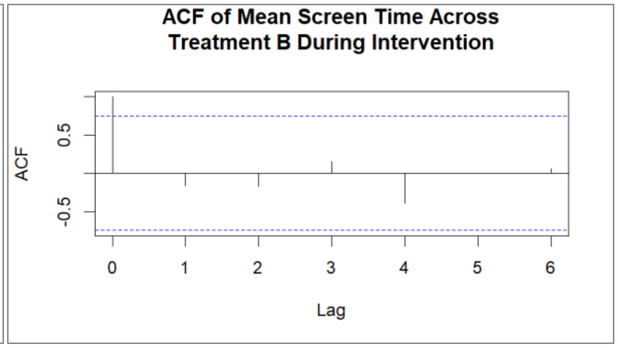
Red = Treatment A; Turquois = Treatment B.





Appendices 9-10. ACF Plots of Mean Screen Time by Phase.





Appendices 11-12. ACF Plots of Mean Screen Time by Treatment During Intervention.