**CSCI.4923 Capstone in Interprofessional Informatics**

**Analysis and Conclusion**

Sachin Karki

Texas Woman’s University

Denton, Texas

Author Note

Sachin Karki, Texas Woman’s University, Mathematics & Computer Science

**Introduction**

The crucial part of any research or study is to explore evidence to interpret findings and reach conclusions. Research involving statistical evidence needs analysis for sure. In this case, testing and analyzing the dataset is necessary to extract and retrieve any information that helps in answering our research question. Our datasets, as mentioned and described previously *Effects.xlsx, Activity.xlsx and Scores.xlsx* will be analyzed extensively with different tools and procedures to test our hypothesis and check the association with other related variables. The outcome of the analysis will help in answering the following research questions.

1. What personal habits (i.e. smoking, alcohol drinking, and religious practices) candidates have that were susceptible to excessive smartphone usage?
2. For what activities (i.e. texting, calling, reading news, entertainment, other reasons) of smartphones led to excessive usage?
3. Is there any relationship between different effects (i.e. decrease in sleep quality, ability to stop worrying, not being able to enjoy a meal) and personality types (i.e. Type A and B)?
4. Which personality type (i.e. Type A or B) is more vulnerable to the effects (i.e. anxiety, compulsive behavior, functional impairment) of excessive smartphone usage?

This paper is an in-depth exploration and interpretation of the analysis and its results.

**Methods and Procedures**

The original dataset was huge with its content, so it was necessary to split and create new datasets to ease the overall analysis. From the original datasets, three new datasets were created, i.e. *activity.xlsx, effects.xlsx, and score.xlsx.* As mentioned previously, these three datasets consist only of the variables that are relevant and meant to generate a specific result out of them. So, each dataset has a purpose of its own. To answer our research question, we would need to select a dataset and then proceed with a method or approach that has the best chance of retrieving the precise results. There are two preferred types of analysis for this research, statistical and visual. The first three questions will be answered with statistical analysis while the last question will be answered with visual analysis. As the majority of our analysis is statistical, it is important to break down the statistical method that would be applied to answer our questions. Answering our question will require a multi-layered approach of analysis. Each layer or step of analysis will determine a unique insight which will be used later with other variables to test different outcomes likes variable dependency, association, correlation, and regression.

Here’s the breakdown of various forms of analysis.

1. Variable dependency check with Correlation Matrix
2. Mean comparison with Cohen’s D
3. Variable selection with Akaike Information Criterion (AIC) and Error rate reduction with Backward Algorithm
4. Association between dependent and independent variables with Multinomial Regression.

**Description and Interpretation of Analysis**

As mentioned previously, the analyses were based on statistical and visual findings. Using the three datasets that were created and curated from the original datasets, various methods mentioned earlier were used. For the statistical analysis, RStudio (R programming language) is used meanwhile the visual analysis used Tableau.

1. **Statistical Analysis of Question 1, 2 and 3**

Statistical methods were taken in order to answer the first three questions. The *activity.xlsx* was used to answer questions 1 and 2 and the *effects.xlsx* was used to answer the third. A Series of conclusions were drawn from both datasets by utilizing various procedures of the multi-layered approach and here’s the exploratory breakdown of both datasets.

1. ***Analysis of Activity.xlsx (To answer questions 1 and 2)***

First and foremost a correlation matrix was generated to check the dependency between the variables. It is only after we know for sure if a relationship exists between the variables, we can proceed further. At this point the dataset has not been filtered out for any missing data in the dataset so the empty values were treated as the default “Not Available (NA)” by default R procedure to generate a correlation matrix.

***Fig 1: Correlation matrix of activity.xlsx dataset***

The given plot above is the summary of correlation coefficients of a different set of variables. It can be noticed that variables “CallFamMem” and “CallFrnds” have a strong positive relationship. The visible and noticeable intensity of the blue dot tells us that they share strong positive relations and logically speaking they attribute somewhat similar activity of smartphone use. Calling friends and calling family members can be considered as a single variable of just calling in general. Therefore, no analysis is needed for this variable since we found a relation among them. The rest of the variables however display a curious pattern so we will proceed with a few more steps to extract conclusions. The code for the correlation matrix is depicted below.

This can be further elaborated by the Spearman coefficient score depicted below

***Fig 2: Correlation graph of activity.xlsx dataset***

From the correlation graph above, we can notice that variables “CallFamMem” and “CallFrnds” have a Spearman score of 0.73 which represents an above-average number on a scale of 1 so statistically speaking these two variables do not have to be included further for more testing.

This was generated using a basic *tidyverse* package in R and the code is depicted below.

In addition to this, our dataset has missing data as well. The number of participants choosing not to respond on a certain topic is very prominent and as a result, we have variables with simply no input. Missing data should always be statistically identified and filtered out to avoid high bias in the results. Using the *ggplot* package in R, missing values were identified, and here’s a visual look at the number of missing data.

***Fig 3: Bar graph of missing data in activity.xlsx datasets***

From the graph above it can be verified that the variables like “Rlgn\_Prctces” and “Study\_Purposes” have the highest count of missing data. “Rlgn\_Prctces” has a total of 227 and “Study\_Purposes” has a total of 275 missing data. Thus, they will be excluded from the analysis since they are likely to cause bias.

The second step of the analysis is to do a mean comparison with Cohen’s D. This will help us determine the effect size between our variables.

***Fig 4: Summary of standard mean difference with Cohen’s D by personality type***

Cohen’s D helps measure the size effect of variables and accompanies additional tests like t-test and ANOVA. A value of 0.2 is considered a small effect size in Cohen’s D and from our result above the variable “smoking” has a standard mean difference of 0.2 in personality type. This means that the variable “smoking” is statistically significant in both personality types.

The third step of our analysis is variable selection. To do so, AIC with a backward algorithm was used to select variables and reduce the error rate. AIC is an estimator of prediction error. The lower the AIC model is, the better it is for our analysis. First variable selection was done with variables like “ID” and “CallFrnds” since the “CallFrnds” retained the highest correlation of 0.73 to the variable “CallFamMem”. This secures the independence of variables. Additionally, “Smoking”, “AGE”, “Study\_Purposes” were used since they retained a reduced AIC of 503 from the original value of 521.69. Like mentioned earlier, the lower the better. Here’s a look at the procedure and result.

***Fig 5: AIC with a backward algorithm***

The final model above suggests that a one-point increment in age will give us a 0.88 odd ratio (OR) increase in both personality types. Smoking is the strongest factor with an odds ratio of 1.78. Each result was accompanied by a p-value of 0.05 significance.

Furthermore, multinomial regression was used on the variable “ExcessveSmrtPhn\_Use” as it has four levels of response denoting the general admittance of excessive smartphone usage by the participants. Here’s the index of the scale used for four levels of response.

1 = strongly disagree, 2 = somewhat disagree, 3 = somewhat agree, 4 = strongly agree,

To conduct regression, variables like, “ID”, “Study\_Purposes”, and “Rlgn\_Prctces”, are excluded, because “ID’ is irrelevant and “Study\_Purposes” and “Rlgn\_Prctces” has a high count of missing data. This helps in avoiding biased results.

Multinomial regression requires comparing with a reference in order to test the outcome of different variables. In our case response levels, 1 and 4 (strongly agree and strongly disagree) will be used as a reference to compare with other response levels since response levels 1 and 4 indicate strong denial and admittance respectively of participants with their excessive smartphone usage. Here’s a code and the result from response level 1.

***Fig 7: Multinomial regression on response level   
4 at 0.05 significance level***

***Fig 6: Multinomial regression on response levels 2 and 3 at 0.05 significance level***

Similarly, here’s the outcome from response level 4.

***Fig 8: Multinomial regression on response levels 1 and 2 at 0.05 significance level***

***Fig 9: Multinomial regression on response level 3 at 0.05 significance level***

Presented results above are done at a significance level p < 0.05. The collective summary of our multinomial regression on all three-response levels (i.e. 1, 2, 3, 4) with respect to response levels 1 and 4 indicates the following insights.

From response level 1

* “Entertainment” had the highest odds ratio in all response levels 2, 3, 4 with a value of 1.48, 2.79, and 2.46 respectively.
* “OthRsns” had the second-highest odds ratio in all response levels 2, 3, 4 with a value of 1.50, 1.73, and 2.64 respectively.
* “RdNews” retained odds ratios of 1.18, 0.82, and 0.91 in response levels 2, 3, 4 respectively.
* “Txtng” retained the least odds ratio among response levels 2, 3, 4 with a value of 0.74, 1.26, and 1.85 respectively.

From response level 4

* “RdNews” had the highest odds ratio in response levels 1 and 2 with a value of 1.10 and 1.30 respectively.
* “Entertainment” had the odds ratio of 0.41, 0.60, and 1.13 in response levels 1, 2, and 3 respectively.
* “Txtng” retained the second-highest odds ratio in response level 1 with a value of 0.54.
* Txtng” also retained the least odds ratio in response levels 2 and 3 with a value of 0.40 and 0.68 respectively.
* “OthRsns” had an increasing odds ratio in response levels 1, 2, and 3 with a value of 0.38, 0.57, 0.65.

From the referential analysis on a different response level, it was found that Entertainment had the highest odds ratio in both response levels. Following up, other reasons retained the second-highest odds ratio. On response level 4, reading news has the highest odds ratio with reference to levels 1 and 2. Texting consistently retained the least odd ratio in both response levels 1 and 4. Lastly, Other reasons showed an increasing trend on both response levels 1 and 4.

Based on the insights generated above, Entertainment and other reasons were the two major contributing factors in excessive smartphone usage among participants. Entertainment retained values of more than 1.0 which shows a strong association among participants and other reasons shows a promising trend as its value are consistently increasing among various response level. Texting was surprisingly not a contributing factor since its odds ratio was least most of the time.

1. ***Analysis of Effects.xlsx (To answer question 3)***

First of all, a correlation matrix was generated to check the variable dependency. It was found that variables like “TotAddiction\_Score”, “Compulsive\_Behaivor”, “Depression\_Score”, “Anxiety\_score” and “Functional\_Impairment” correlated with high scores. Here’s a look at the code and correlation matrix and correlation graph and that was used in R.

***Fig 10: Correlation matrix of effects.xlsx dataset***

From the correlation matrix above, it can be noticed that variables like “TotAddiction\_Score”, “Compulsive\_Behaivor”, “Depression\_Score”, “Anxiety\_score” and “Functional\_Impairment” show a high correlation. The dependency test on these variables can be skipped for further variable selection. This data can also be illustrated with the Spearman correlation score below.

***Fig 11: Correlation graph of effects.xlsx dataset***

From the correlation graph above, we see a lot of the variables as mentioned earlier show a high correlation with each other. Variables like “TotAddiction\_Score”, “Compulsive\_Behaivor”, “Depression\_Score”, “Anxiety\_score” and “Functional\_Impairment” have a high correlation with each other. It can be observed that “Compulsive\_Behaivor” and “TotAddiction\_Score” have a high correlation of 0.95. Similarly, “TotAddiction\_Score” and “Functional\_Impairment” show a high correlation of 0.90 with each other. These highly correlated variables will not be needed for our analysis since they do not pose any relevance to the question our analysis is trying to answer.

Moving on, the missing values within the dataset were visualized. The *ggplot* package of R was utilized to do so and here are the results.

***Fig 12: Bar graph of missing values from effects.xlsx dataset***

From the graph above, it can be seen that the number of missing data in most of the variables like “Anxiety \_score”, “Feel\_Deprssd”, “Lttl\_IntrstDoingThngs” etc. are well over 200. We will not exclude them for further analysis since the exclusion will leave us with few variables for the analysis from which the accuracy of the result can be compromised.

Following up, a mean comparison with Cohen’s D was performed on the *effects.xlsx* dataset to measure the size effects of variables. This process is similar to what was done with the *activity.xlsx* dataset. The code and results are illustrated below.

***Fig 13: Summary of standard mean difference with Cohen’s D by personality type in effects.xlsx dataset***

From the collective results generated by the Cohen’s D procedure above, the variables

“DecreasdTmeSlpQulty\_SmrtPhneUse”,” CannotHveMeal\_NosmrtPhn” “Compulsive\_Behavior” and “Functional\_Impairment” retained a perfect size effect of 0.2. This means that these variables are statistically significant in the *effects.xlsx* dataset.

Furthermore, AIC with a backward algorithm was used for variable selection.

Variables with a larger size effect were selected alongside a variable with a perfect size effect. Since “Lttl\_IntrstDoingthngs” and “NotAble\_Stpworry” retained a size effect of 0.306 and 0.523 respectively they were used for AIC alongside “CannotHveMeal\_NoSmrtPhn” which retained a perfect size effect of 0.288. The code and outcomes of the procedures are illustrated below.

***Fig 14: AIC with a backward algorithm in effects.xlsx dataset***

In the AIC analysis done above, a few observations were made.

* 1.69 odd ratio with “CannotHveMeal\_NosmrtPhn” by personality 0 to 1
* NotAble\_Stpworry shows a notable odd ratio between its level from 2 (OR: 5.3) to Personality type
* Model is significant that in-between final variables, there are relevant predictors to variable “Prsnlty\_type”

To summarize our analysis from a visual perspective, here’s a resulting violin plot that was generated in R.

***Fig 15: Violin plot of selected variables in different personality types***

In the violin plot illustrated above, we can see the x-axis represents the variable “NotAble\_Stpworry” meanwhile the y-axis represents the variable “CannotHveMeal\_NoSmrtPhn”. The violin plot depicts these variables in terms of personality types 0 and 1. Personality type 1 has more thickness and spread out than personality type 0. It would be safe to say that the effect of excessive smartphone usage like not being able to stop worrying and inability to enjoy a meal has more impact on personality type 1.

1. **Visual Analysis of Question 4**

The visual analysis was done on the *scores.xlsx* dataset using the visualization software Tableau. Scores dataset consists of variables relating to different symptoms that participants admitted of experiencing. Variables like “Compulsive\_Behavior”, “Functional\_Impairment”, “Feel\_Depressed” are used to represent the psychological aspect of participants. In the original dataset and its analysis (Boumosleh & Jaalouk, 2017) these variables were used to denote the Smart Phone Addiction Indicator (SPAI) scale. SPAI is the cumulative score of a variable derived using the mean difference and Chi-square. The new visualization that was generated using the new dataset is a mere visual portrayal and depiction of the SPAI with a minor modification in the values. The personality type 0 was changed to A and 1 was changed to B to make it easier to comprehend and explain the results. No other changes were made.

In Tableau, the *scores.xlsx* was located, the first and foremost challenge in extracting visuals was to correctly identify the dataset and its attributes. Categorical values like our dataset always need a few modifications to use them properly and effectively. For an instance, even though our dataset has numerical values that denote the count of a number they are not properly configured to be used as the whole number so the data type needs to be changed. In our case, the data type was changed to a numeric whole number and a few variables were converted to dimension to achieve the right and appealing set of bar graphs. From this dataset, we are trying to find effects and the difference in vulnerabilities among two personality types. Bar graphs and a dashboard were generated, to sum up, the visualization. Results are depicted below.

***Fig 16: Bar graph of the variable “Depression\_score” on two personality types.***

In the depicted graph above, we can see that personality type B has a high score on the variable “Depression \_score” from the SPAI scale. This hints that personality type A is less susceptible to the effects of excessive smartphone usage.

***Fig 17: Bar graph of “Anxiety\_score” on two personality types***

In the depicted bar graph above personality type B has the count of 445 in “Anxiety\_score” from the SPAI scale. Personality type A following up close but nowhere near to personality B. This makes personality type A less susceptible to the effects of excessive smartphone usage. Meanwhile, personality type B is more susceptible to effects of the excessive smartphone use.

***Fig 18: Bar graph of “Compulsive\_Behavior” among two personality types***

From the illustrated bar graph above, it can be seen that personality type B has a whopping 5792 score from the SPAI scale. Personality type A has a score of 3500. Statistically speaking personality type B is 60% more likely to be affected with compulsive behavior as a result of excessive smartphone usage.

***Fig 19: Bar graph of “Functional\_impairment” among two personality types***

Again, personality type B has the highest score of 5350 on the SPAI scale. Personality type A sums up to around 3100 making it about 57% less likely to be affected with functional impairment as a result of excessive smartphone usage.

**Meaning, Association and Summary of Analysis with Research Questions**

From our multi-layered analysis of the datasets, a lot of results were produced. Inspection and filtration were done to extract only the meaningful, accurate, and relevant results. Not every method that was utilized returned expected results. To begin with, we had three major variables that represented the personal habits of the candidates i.e. “Rlgn\_Prctces”, “Smoking” and “Alcohol\_drnk” from the *activity.xlsx* dataset. Early on “Rlgn\_Prctces” was taken out from the further analysis since it had the highest count of missing data so technically the chances of that variable helping in answering one of our research questions was very minimal. When proceeded further with Cohen’s D only “Smoking” had a perfect size effect of 0.2 and “Alcohol\_drnk” retained a lower value of 0.021.

Furthermore, “Smoking” returned a higher odd ratio in AIC and consistently better in multinomial regression with 0.33, 0.51, and 0.66 in response level 1. The increasing odds ratio tells us that the slightest change in the “Smoking” variable is likely to cause a shift in the overall analysis. Therefore, it can be concluded that among the three variables of interpersonal behaviors, Smoking highly contributes to excessive smartphone usage. Drinking alcohol is less likely to have a higher effect on excessive smartphone usage although it does contribute in a minor way. Religious practices have almost zero or insignificant effect in causing excessive smartphone use.

Similarly, from the second Cohen’s D on the *effects.xlsx* dataset, it was found that variables like “DecreasdTmeSlpQulty\_SmrtPhneUse”, “Compulsive\_Behavior” and “Functional\_Impairment” retained a perfect size effect of 0.2 out of all other variables. It can be summed up that the effects of excessive smartphones like a decrease in quality sleep time, compulsive behavior, and functional impairment are higher than any other mentioned effects. The Standard Deviation of personality type 1 or B in three variables was also found to be more causing higher variance. Following up close on the similar pattern are variables like “CannotHveMeal\_NosmrtPhn”, “Lttl\_IntrstDoingThngs” that showed a promising trend. “NotAble\_Stpworry” returned a higher size effect value so to further analyze these variables AIC procedure was conducted. Although no significant insights were found with the procedure but generating a violin plot (Fig 15) tells us that personality type 1 or B are likely to have effects like not being able to have a meal without a smartphone and inability to stop worrying. These variables compared to the ones from Cohen’s D can be weak since they initially did not show a perfect size effect, but they do have minimal to broad effect over excessive smartphone use.

Furthermore, the multinomial regression on the *activity.xlsx* dataset concluded that variables like “Entertainment” and “OthRsns” showed a consistently increasing pattern on each response level (Fig 6,7,8,9,10). “Txtng” was not the most prominent variable. In other words, texting was not seen to be strongly associated with excessive smartphone usage.

Additionally, from the Cohen’s D on the *activity.xlsx* dataset, personality type 1 or B generated higher Standard Mean Difference than type 0 or A which in general can be said that type 1 just has a higher effect on the activities than type 0. Lastly, the visualizations generated from the *scores.xlsx* dataset in Tableau are obvious as the illustrations are very precise and simple. The SPAI score of different variables shows how the variable compare against each other in different personality types. Illustrations depicted above, figure 16, 17, 18, and19 summarize that personality type 1 or B is likely to score more on the SPAI scale of different effects of excessive smartphone usage. This tells us that personality type 1 or B is more vulnerable to the effects of excessive smartphone usage.

**Limitation and Potential of the Analysis**

As it’s known, the original dataset was raw when it was retrieved initially so the possibilities with the original dataset are endless. Our analysis is also an instance of one of those possibilities since a new dataset was created by splitting required variables. This not only helped to conduct the required analysis but also to reach conclusions and answer the research questions. However, even our study and the analysis have a few limitations that were not addressed or explored.

For an instance, the variable “smoking” was found to be strongly linear to excessive smartphone usage. This is to say that group of people who admitted smoking as an interpersonal habit are prone to be addicted to excessive smartphone use. However, it is not clear what category of smokers (i.e. heavy, light, or chain smokers) are more likely to be excessive smartphone users. This is by default one of the limitations of the dataset and analysis we performed.

Another instance of such limitation is that our dataset does not have any information or explanation on some of the effects that participants had because of excessive smartphone use. For example, the original dataset and the one we created contains variables like “compulsive behavior”, “depression”, “anxiety”, “functional impairment” etc. but the values for these variables were generated based on the candidate's admission or denial on the respective topic. A classic yes or no type of response could be ineffective for a broad subject that those variables are representing. We are not given or told the contributing factors of those variables and it can be biased since any candidate on a given day may give a different response on a specific topic depending on their mood.

In addition to this, other forms of analysis can be done with our dataset to answer more questions. For an instance, a possible question can be related to finding a connection between texting and anxiety in both personality types, finding if there exists any relationship between participants who are depressed see using a smartphone as entertainment purpose as a cause of depression, finding the relationship between compulsive behavior and the number of people who admit smoking can lead to excessive smartphone usage and then comparing it against with people who deny, etc.

Using two or more multi-layered approaches of analysis can help in finding the answers to the questions mentioned above. New dataset creation with relevant variables can be a starting point.

**Comparing and Contrasting with Primary Research**

In a lot of ways, our study concurs with as well as differs from the primary research.   
First of all, the primary research was specifically focused on finding if any relationship exists between depression, anxiety, and smartphone usage, and our study was specifically based on exploring the adverse effects of smartphone usage by analyzing certain and limited variables from the original dataset. In hindsight, our study is a new iteration of the primary research that was not addressed or explored.

The primary research utilized a different set of tests to achieve mathematical and statistical results. Descriptive statistics, qualitative and quantitative measurements like mean, standard deviation, independent 2 sample T-Test, Chi-Square, and multilinear regression were effectively used whereas our study took a similar approach with added AIC method and multinomial regression for variable selection and variable association respectively.

A common element between the primary research and our study was the use of p-value at less than 0.05 to ensure the computation of strong evidence. Both studies effectively utilized Spearman correlation coefficients to evaluate the association among the different dependent and independent variables. However, both studies did not use the same tool to analyze and conclude the results, the primary research used Statistical Package for Social Sciences (SPSS) whereas our study used R programming language.

The most notable and mutual similarity in both studies was the conclusion that personality type 1 or B were most susceptible to excessive smartphone use.

In addition to this, there were key differences in terms of the limitation of each study.   
The primary study does not explicitly describe how candidates were anxious or stressed using smartphones. A typical yes or no survey was carried out to have participants admit or deny if they have anxiety, stress, or depression. This procedure could be ineffective as it is very subjective and not based on any scientific evidence. Self-reporting a psychological aspect is not a precise way of drawing conclusions.

Whereas in our study, a detailed description of a few variables is not given. As mentioned previously, for the variable “smoking” we are not told or given the category of smokers. This is crucial since our analysis found that people who smoke are prone to be addicted to excessive smartphone usage but not all people have the same smoking preference, some are light smokers while some are heavy. This leads to instill that people who smoke in general are addicted to smartphone usage in general. One of the main differences is that the primary research fully utilizes the original dataset by using methods to test all its variables meanwhile our study partially utilizes and draw new conclusions. In addition to differences, the primary research addresses missing values by treating them as an outlier without using any method, but our study uses the built-in R procedure to treat missing results as “NA” variable to make it compatible for R to run the analysis and to reduce biases

**Conclusion**

After analyzing the dataset using a multi-layered approach with various methods, we have gleaned results from the analysis to answer our research questions. The main goal of this study was to correctly identify the problem of excessive smartphone use and explore its adverse effects. From ranges of personal habits (i.e. drinking alcohol, smoking, and religious practices) in the *activity.xlsx* dataset, smoking was found to have a strong relationship with excessive smartphone usage smart people. Drinking alcohol follows up as a second personal trait that is somewhat associated with excessive smartphone usage meanwhile religious practices were found to have no association, therefore, posing no effect in excessive smartphone usage.

Similarly, entertainment and other reasons showed a strong association among participants who admitted to excessive smartphone usage. Texting followed up closely but did not have a solid impact compared to any other variable.

From the *effects.xlsx* dataset, it was found that participants who excessively use smartphones highly experience effects like a decrease in sleep time, inability to enjoy a meal, general loss of interest in doing things, and ability to stop worrying. Among which the decrease in sleep time quality overall had a strong association with other independent variables that proved one of the major adverse effects of excessive smartphone use is loss of sleep or insomnia. Other variables of effects mentioned above also had a good level of association with other variables and they were mostly found on participants with personality type 1 or B.

Lastly, the personality type with a noted high majority of psychological changes like compulsive behavior, functional impairment, anxiety, and depression are type B which suggests that personality type B are likely to be more vulnerable and susceptible to excessive smartphone use.

**References**

Boumosleh, J. M., & Jaalouk, D. (2017). Depression, anxiety, and smartphone addiction in university students- A cross sectional study. PLOS ONE 12(8): e0182239. <https://doi.org/10.1371/journal.pone.0182239>

Boumosleh, J. M., & Jaalouk, D. (2017). *Raw data for all participants*. (Version 1). PLOS ONE. <https://doi.org/10.1371/journal.pone.0182239.s001>

Arumugam, N., Selvanayagam, S., & Sathiyasenan, S. T. (2020). The Effects of Smartphone Usage on University Students. *International Journal of Academic Research in Progressive Education and Development*, 9(3), 170–183. : <http://dx.doi.org/10.6007/IJARPED/v9-i3/7960>