# Midterm Exam

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11/2/2020

### Instruction

This is your midterm exam that you are expected to work on it alone. You may NOT discuss any of the content of your exam with anyone except your instructor. This includes text, chat, email and other online forums. We expect you to respect and follow the GRS Academic and Professional Conduct Code.

Although you may NOT ask anyone directly, you are allowed to use external resources such as R codes on the Internet. If you do use someone's code, please make sure you clearly cite the origin of the code.

When you finish, please compile and submit the PDF file and the link to the GitHub repository that contains the entire analysis.

### Introduction

In this exam, you will act as both the client and the consultant for the data that you collected in the data collection exercise (20pts). Please note that you are not allowed to change the data. The goal of this exam is to demonstrate your ability to perform the statistical analysis that you learned in this class so far. It is important to note that significance of the analysis is not the main goal of this exam but the focus is on the appropriateness of your approaches.

#### Data Description (10pts)

# Load and read my data into R

Please explain what your data is about and what the comparison of interest is. In the process, please make sure to demonstrate that you can load your data properly into R.

```
## The introduction of my data

## hair_loss: When I took the survey, I set a 6 points scale to assess the severity of hair loss of res

## gender: "1" indicates female, "0" indicates male.

## age: "1" indicates 18-25 years old, "2" indicates 26-40 years old, "3" indicates more than 40 years

## insommia: "1" indicates that respondents have insommia, "0" indicates no insommia.

## sleep_t: The average daily sleeping time. "1" indicates less than 4 hours, "2" indicates 4-6 hours,

## computer_t: The average daily computer facing time. "1" indicates less than 1 hour, "2" indicates 1-2 hours, "3"

## sport_t: The average daily sport time. "1" indicates less than 1 hour, "2" indicates 1-2 hours, "3"

## genetic: "1" indicates that the respondent has family hereditary hair loss, "0" indicates none.

## pregnant: "1" indicates that the respondent is in the post-pregnancy stage, "0" indicates none.

## menopause: "1" indicates that the respondent is menopause, "0" indicates none.

## chemical: "1" indicates that the respondent has used poor quality hair dye or perm, "0" indicates none.

## disease: "1" indicates that the respondent has hair follicle disease, "0" indicates none.

## The comparison of interest

## Given the information of different respondents such as their gender, age, having insommia or not and
```

hairloss <- read.csv("https://raw.githubusercontent.com/VivianXu66/Midterm\_Exam/main/collection.csv",hehead(hairloss)

##		X hair_los	ss gender	age	insomnia	sleep_t	computer_t	sport_t	genetic	pregnant
##	1	1	1 1	. 1	1	3	2	2	0	0
##	2	2	0 (	) 1	0	3	3	1	0	0
##	3	3	0 1	. 1	0	3	1	4	0	0
##	4	4	0 (	) 1	1	3	5	1	0	0
##	5	5	0 (	) 1	0	4	3	1	0	0
##	6	6	0 (	3	0	3	4	1	0	0
##		menopause	chemical	dis	ease					
##	1	0	1		0					
##	2	0	(	)	0					
##	3	0	(	)	0					
##	4	0	(	)	0					
##	5	0	(	)	0					
##	6	0	(	)	0					

# EDA (10pts)

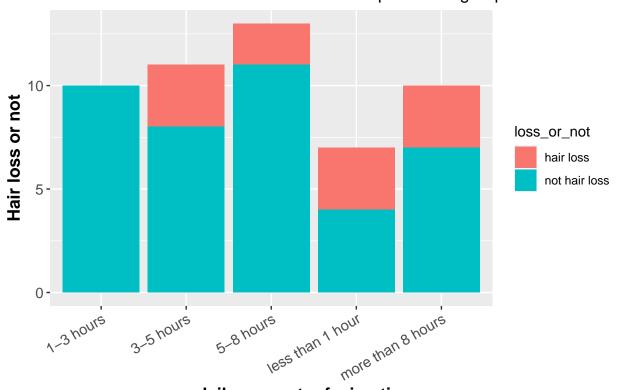
Please create one (maybe two) figure(s) that highlights the contrast of interest. Make sure you think ahead and match your figure with the analysis. For example, if your model requires you to take a log, make sure you take log in the figure as well.

### summary(hairloss)

```
X
##
                       hair_loss
                                            gender
                                                               age
                             :0.0000
                                               :0.0000
##
    Min.
           : 1.00
                     Min.
                                       Min.
                                                          Min.
                                                                 :1.00
##
    1st Qu.:14.75
                     1st Qu.:0.0000
                                       1st Qu.:0.0000
                                                          1st Qu.:1.00
##
    Median :28.50
                     Median :0.0000
                                       Median :1.0000
                                                          Median:1.00
##
    Mean
            :28.50
                     Mean
                             :0.2679
                                       Mean
                                               :0.6071
                                                          Mean
                                                                 :1.75
##
    3rd Qu.:42.25
                     3rd Qu.:1.0000
                                       3rd Qu.:1.0000
                                                          3rd Qu.:3.00
            :56.00
                             :1.0000
##
    Max.
                     Max.
                                       Max.
                                               :1.0000
                                                          Max.
                                                                 :3.00
##
       insomnia
                         sleep_t
                                          computer_t
                                                            sport_t
##
    Min.
            :0.0000
                      Min.
                              :1.000
                                       Min.
                                               :1.000
                                                                :1.000
##
    1st Qu.:0.0000
                      1st Qu.:3.000
                                       1st Qu.:2.000
                                                         1st Qu.:1.000
                      Median :3.000
                                                         Median :1.000
##
    Median :0.0000
                                       Median :3.000
##
    Mean
            :0.2679
                              :2.946
                                               :3.071
                                                                :1.518
                      Mean
                                       Mean
                                                         Mean
##
    3rd Qu.:1.0000
                      3rd Qu.:3.000
                                       3rd Qu.:4.000
                                                         3rd Qu.:2.000
                                               :5.000
##
    Max.
            :1.0000
                              :4.000
                      Max.
                                       Max.
                                                         Max.
                                                                :4.000
       genetic
                          pregnant
                                      menopause
##
                                                           chemical
                               :0
                                            :0.00000
                                                               :0.00000
##
    Min.
            :0.00000
                       Min.
                                    Min.
                                                        Min.
##
    1st Qu.:0.00000
                       1st Qu.:0
                                    1st Qu.:0.00000
                                                        1st Qu.:0.00000
                                                        Median :0.00000
##
    Median :0.00000
                       Median:0
                                    Median :0.00000
##
    Mean
            :0.03571
                       Mean
                               :0
                                    Mean
                                            :0.01786
                                                        Mean
                                                               :0.01786
##
    3rd Qu.:0.00000
                       3rd Qu.:0
                                    3rd Qu.:0.00000
                                                        3rd Qu.:0.00000
##
    Max.
            :1.00000
                       Max.
                               :0
                                    Max.
                                            :1.00000
                                                        Max.
                                                               :1.00000
##
       disease
##
            :0.0000
    Min.
##
    1st Qu.:0.00000
##
    Median :0.00000
##
    Mean
            :0.01786
##
    3rd Qu.:0.00000
##
    Max.
            :1.00000
```

```
# Simply organize the data
## According to common sense, the predictor "genetic", "pregnant", "menopause", "chemical" and "disease
hairloss <- subset(hairloss, hairloss $genetic == "0" khairloss pregnant == "0" khairloss menopause == "0" khairlo
hairloss \% select(-c(1,9:13))
rownames(hairloss) <- c(1:51)</pre>
# There are many predictors in this data. I want to operate EDA on the predictor "computer_t" and the o
## Firstly, get the counts of hair loss or not in different computer_t groups.
bar_data <- hairloss %>% group_by(hair_loss,computer_t) %>% summarise(Count=n())
## `summarise()` regrouping output by 'hair_loss' (override with `.groups` argument)
## Plot the stacked bar
computer_time <- c(rep("less than 1 hour",2),rep("1-3 hours",2),rep("3-5 hours",2),rep("5-8 hours",2),r
loss_or_not <- rep(c("hair loss","not hair loss"),5)</pre>
value \leftarrow c(3,4,0,10,3,8,2,11,3,7)
data <- data.frame(computer_time,loss_or_not,value)</pre>
ggplot(data,aes(fill=loss_or_not,y=value,x=computer_time)) +
           geom_bar(position="stack",stat="identity")+
     theme(axis.text.x=element_text(angle=30,hjust=1),
                     axis.text=element_text(size=11),
                     axis.title=element_text(size=13,face="bold"))+ggtitle("The counts of hair loss or not for each
```

# The counts of hair loss or not for each computer time group

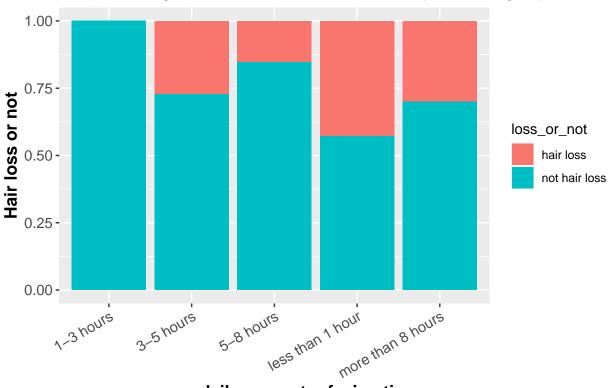


# average daily computer facing time

```
## Plot the percentage stacked bar
ggplot(data,aes(fill=loss_or_not,y=value,x=computer_time)) +
    geom_bar(position="fill",stat="identity")+
```

```
theme(axis.text.x=element_text(angle=30,hjust=1),
         axis.text=element_text(size=11),
         axis.title=element_text(size=13,face="bold"))+ggtitle("The percentage of hair loss or not for e
```

# The percentage of hair loss or not for each computer time group



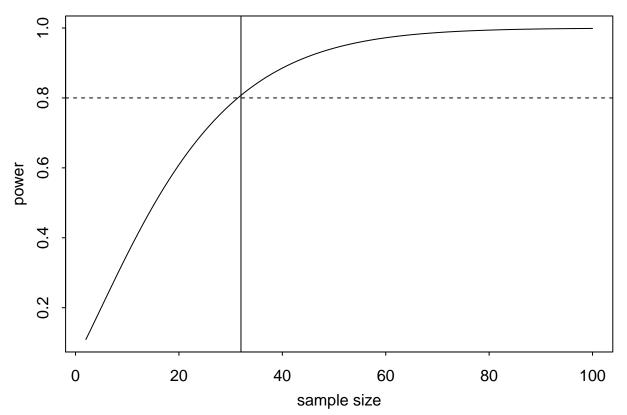
average daily computer facing time

# Power Analysis (10pts)

Please perform power analysis on the project. Use 80% power, the sample size you used and infer the level of effect size you will be able to detect. Discuss whether your sample size was enough for the problem at hand. Please note that method of power analysis should match the analysis. Also, please clearly state why you should NOT use the effect size from the fitted model.

```
# Use the function in pwr package to perform power analysis
pwr.p.test(h=NULL,n=51,sig.level=0.05,power=0.8)
##
##
        proportion power calculation for binomial distribution (arcsine transformation)
##
##
                 h = 0.3923029
##
                 n = 51
##
         sig.level = 0.05
##
             power = 0.8
##
       alternative = two.sided
## The effect size h = 0.3923029
# Cohen suggests that h values of 0.2, 0.5, and 0.8 represent small, medium, and large effect sizes res
```

```
par(mar=c(3,3,2,1), mgp=c(2,.7,0), tck=-.01)
nlist<-2:100
powres<-sapply(nlist,function(x)pwr.p.test(n=x,h=0.5,sig.level=0.05,NULL)$power)
plot(nlist,powres,type="l",xlab="sample size",ylab="power");abline(h=0.8,lty=2); abline(v=nlist[which(p)])</pre>
```



## From the plot, we can see that if effect size is medium and power is above 0.8, we need to ensure the # Effect size is usually hypothesized due to the unknown true value.

# Modeling (10pts)

Please pick a regression model that best fits your data and fit your model. Please make sure you describe why you decide to choose the model. Also, if you are using GLM, make sure you explain your choice of link function as well.

```
## stan_glmer
## family: binomial [logit]
## formula: hair_loss ~ gender + insomnia + (1 | age) + (1 | sleep_t) + (1 |
## computer_t) + (1 | sport_t)
## observations: 51
## -----
## Median MAD_SD
## (Intercept) -4.1 1.6
```

```
## gender
                3.1
                       1.3
## insomnia
                1.7
                       1.0
##
## Error terms:
## Groups
               Name
                           Std.Dev.
## computer_t (Intercept) 1.46
## sport_t
               (Intercept) 0.83
               (Intercept) 0.99
## sleep_t
## age
               (Intercept) 1.09
## Num. levels: computer_t 5, sport_t 4, sleep_t 4, age 3
##
## ----
## * For help interpreting the printed output see ?print.stanreg
## * For info on the priors used see ?prior_summary.stanreg
ranef(fit)
## $computer_t
##
     (Intercept)
## 1
      0.4580832
## 2 -1.1559754
## 3
     0.2804530
## 4 -0.1730039
       0.1093094
## 5
##
## $sport_t
##
      (Intercept)
## 1 0.015331466
## 2 -0.043461565
## 3 -0.019621323
## 4 0.008789071
##
## $sleep_t
##
     (Intercept)
## 1 -0.02237157
## 2 0.08290727
## 3 0.01013896
## 4 -0.08407684
##
## $age
     (Intercept)
## 1 -0.21598645
## 2 0.20485323
## 3 -0.06763606
##
## with conditional variances for "computer_t" "sport_t" "sleep_t" "age"
## This is a multilevel logistic model. Firstly, the outcome in the data is binary so we need to fit a
```

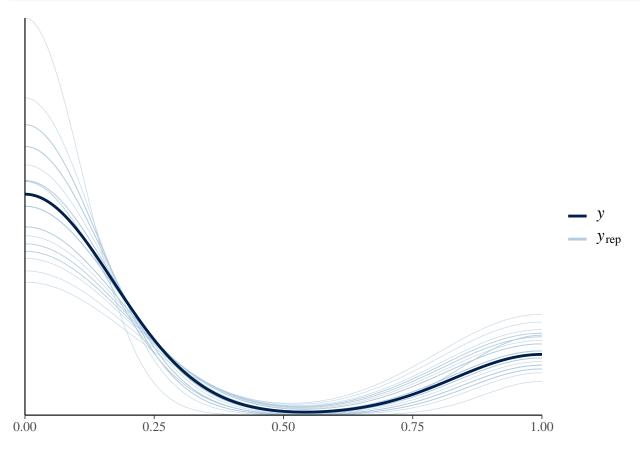
### Validation (10pts)

Please perform a necessary validation and argue why your choice of the model is appropriate.

```
# Leave-one-out cross validation
logis_loo <- loo(fit)
```

```
## Warning: Found 1 observation(s) with a pareto_k > 0.7. We recommend calling 'loo' again with argumen
logis_loo
##
## Computed from 4000 by 51 log-likelihood matrix
##
##
            Estimate
               -26.4 5.2
## elpd_loo
## p_loo
                 8.4 2.3
                52.8 10.4
## looic
## Monte Carlo SE of elpd_loo is NA.
## Pareto k diagnostic values:
##
                            Count Pct.
                                           Min. n_eff
## (-Inf, 0.5]
                             44
                                   86.3%
                 (good)
                                           1307
##
   (0.5, 0.7]
                 (ok)
                              6
                                   11.8%
                                           1344
##
      (0.7, 1]
                 (bad)
                              1
                                    2.0%
                                           125
##
      (1, Inf)
                 (very bad)
                             0
                                    0.0%
                                           <NA>
## See help('pareto-k-diagnostic') for details.
logis_loo_1 <- loo(fit,k_threshold = 0.7)</pre>
## 1 problematic observation(s) found.
## Model will be refit 1 times.
## Fitting model 1 out of 1 (leaving out observation 22)
logis_loo_1
##
## Computed from 4000 by 51 log-likelihood matrix
##
##
            Estimate
                       SE
## elpd_loo
               -26.5 5.2
                 8.5 2.4
## p_loo
## looic
                52.9 10.5
## -----
## Monte Carlo SE of elpd_loo is 0.1.
##
## Pareto k diagnostic values:
##
                            Count Pct.
                                           Min. n_eff
## (-Inf, 0.5]
                 (good)
                            44
                                   88.0%
                                           1307
                              6
                                   12.0%
##
  (0.5, 0.7]
                 (ok)
                                           1344
##
      (0.7, 1]
                 (bad)
                              0
                                    0.0%
                                           <NA>
##
      (1, Inf)
                 (very bad)
                             0
                                    0.0%
                                           <NA>
##
## All Pareto k estimates are ok (k < 0.7).
## See help('pareto-k-diagnostic') for details.
## There is one unstable observation for the first loo. But after refitting the model 1 times, we can s
\# To better excludes the unstable observation in LOO, I use the k-fold cross validation
kfold(fit,K=10)
## Fitting model 1 out of 10
```

```
## Fitting model 2 out of 10
## Fitting model 3 out of 10
## Fitting model 4 out of 10
## Fitting model 5 out of 10
## Fitting model 6 out of 10
## Fitting model 7 out of 10
## Fitting model 8 out of 10
## Fitting model 9 out of 10
## Fitting model 10 out of 10 \,
##
## Based on 10-fold cross-validation
##
              Estimate SE
## elpd_kfold
                 -25.3 4.9
## p_kfold
                    NA NA
## kfoldic
                  50.6 9.8
## The results are similar to that of LOO valiation.
\# plot the posterior predictive checks
pp_check(fit)
```



### Inference (10pts)

## MCMC diagnostics

Based on the result so far please perform statistical inference to compare the comparison of interest.

```
# Summary the inference
summary(fit)
##
## Model Info:
##
  function:
                  stan_glmer
##
   family:
                  binomial [logit]
##
                  hair_loss ~ gender + insomnia + (1 | age) + (1 | sleep_t) + (1 |
##
       computer_t) + (1 | sport_t)
##
                  sampling
  algorithm:
## sample:
                  4000 (posterior sample size)
                  see help('prior_summary')
## priors:
##
    observations: 51
##
    groups:
                  computer_t (5), sport_t (4), sleep_t (4), age (3)
##
## Estimates:
##
                                                             10%
                                                                   50%
                                                                         90%
                                                mean
                                                       sd
                                                                 -4.1
## (Intercept)
                                               -4.2
                                                       1.6 - 6.2
                                                                       -2.2
## gender
                                               3.2
                                                       1.3 1.6
                                                                  3.1
                                                                        5.0
## insomnia
                                               1.7
                                                       1.1 0.4
                                                                  1.7
                                                                        3.1
## b[(Intercept) computer_t:1]
                                               0.7
                                                       1.0 -0.3
                                                                  0.5
                                                                        2.1
## b[(Intercept) computer_t:2]
                                              -1.6
                                                       1.7 -3.8
                                                                 -1.2
                                                                        0.0
## b[(Intercept) computer_t:3]
                                               0.4
                                                       0.9 - 0.5
                                                                  0.3
                                                                        1.6
## b[(Intercept) computer_t:4]
                                              -0.3
                                                       0.9 - 1.4
                                                                -0.2
                                                                        0.7
                                                       0.9 - 0.8
## b[(Intercept) computer_t:5]
                                               0.2
                                                                  0.1
                                                                        1.2
## b[(Intercept) sport_t:1]
                                                       0.6 - 0.6
                                                                  0.0
                                               0.1
                                                                        0.7
## b[(Intercept) sport_t:2]
                                              -0.2
                                                       0.7 - 1.0
                                                                  0.0
                                                                        0.4
## b[(Intercept) sport_t:3]
                                              -0.1
                                                       0.8 -0.9
                                                                  0.0
                                                                        0.5
## b[(Intercept) sport_t:4]
                                               0.0
                                                       0.7 - 0.6
                                                                  0.0
                                                                        0.7
## b[(Intercept) sleep_t:1]
                                                       0.9 - 1.0
                                                                  0.0
                                              -0.1
                                                                        0.6
## b[(Intercept) sleep_t:2]
                                               0.3
                                                       0.8 - 0.4
                                                                  0.1
                                                                        1.2
## b[(Intercept) sleep_t:3]
                                               0.1
                                                       0.6 -0.6
                                                                  0.0
                                                                        0.8
## b[(Intercept) sleep_t:4]
                                              -0.4
                                                       0.9 - 1.4
                                                                 -0.1
                                                                        0.4
                                                                -0.2
                                              -0.5
                                                       0.8 - 1.5
## b[(Intercept) age:1]
                                                                        0.2
## b[(Intercept) age:2]
                                                       0.9 - 0.3
                                                                  0.2
                                               0.5
                                                                        1.6
                                                       0.8 - 1.2
## b[(Intercept) age:3]
                                              -0.2
                                                                 -0.1
                                                                        0.5
## Sigma[computer_t:(Intercept),(Intercept)] 2.1
                                                       3.3 0.0
                                                                  1.0
                                                                        5.3
## Sigma[sport_t:(Intercept),(Intercept)]
                                               0.7
                                                       2.0 0.0
                                                                  0.2
                                                                        1.7
## Sigma[sleep_t:(Intercept),(Intercept)]
                                               1.0
                                                       2.4 0.0
                                                                  0.2
                                                                        2.4
## Sigma[age:(Intercept),(Intercept)]
                                               1.2
                                                       2.3 0.0
                                                                  0.4
                                                                        3.1
##
## Fit Diagnostics:
                           10%
##
              mean
                     sd
                                 50%
                                       90%
## mean_PPD 0.2
                   0.1 0.1
                               0.2
                                     0.3
##
## The mean_ppd is the sample average posterior predictive distribution of the outcome variable (for de
##
```

```
##
                                               mcse Rhat n eff
## (Intercept)
                                                    1.0
                                               0.0
                                                         2604
## gender
                                                    1.0
                                                         3737
## insomnia
                                                    1.0
                                                         3569
                                               0.0
## b[(Intercept) computer_t:1]
                                               0.0
                                                    1.0
                                                         2575
## b[(Intercept) computer_t:2]
                                              0.0
                                                    1.0
                                                         1915
## b[(Intercept) computer_t:3]
                                               0.0
                                                   1.0
                                                         3635
## b[(Intercept) computer_t:4]
                                               0.0
                                                    1.0
                                                         3290
## b[(Intercept) computer_t:5]
                                               0.0
                                                    1.0
                                                         3653
## b[(Intercept) sport_t:1]
                                               0.0
                                                    1.0
                                                         2656
## b[(Intercept) sport_t:2]
                                               0.0
                                                    1.0
                                                         2572
## b[(Intercept) sport_t:3]
                                               0.0
                                                    1.0
                                                         3793
## b[(Intercept) sport_t:4]
                                               0.0
                                                    1.0
                                                         3448
## b[(Intercept) sleep_t:1]
                                               0.0
                                                    1.0
                                                         3411
## b[(Intercept) sleep_t:2]
                                                    1.0
                                                         3158
                                               0.0
## b[(Intercept) sleep_t:3]
                                               0.0
                                                    1.0
                                                         3093
## b[(Intercept) sleep_t:4]
                                               0.0
                                                    1.0
                                                         3172
## b[(Intercept) age:1]
                                               0.0
                                                    1.0
                                                         2410
## b[(Intercept) age:2]
                                               0.0
                                                    1.0
                                                         3764
## b[(Intercept) age:3]
                                               0.0
                                                    1.0
                                                         3185
## Sigma[computer_t:(Intercept),(Intercept)] 0.1
                                                         2186
## Sigma[sport_t:(Intercept),(Intercept)]
                                                         4038
                                               0.0
## Sigma[sleep_t:(Intercept),(Intercept)]
                                               0.0
                                                    1.0
                                                         3672
## Sigma[age:(Intercept),(Intercept)]
                                               0.0
                                                    1.0
                                                         2783
## mean PPD
                                               0.0
                                                    1.0
                                                         3914
## log-posterior
                                               0.1
                                                    1.0
                                                         1110
##
```

## For each parameter, mcse is Monte Carlo standard error, n\_eff is a crude measure of effective sample
## We can see that except for intercept and the coefficient of gender, other coefficients are not signi
# Maybe a prediction simulation is better for inference, but I don't know how to do such a simulation f

# Discussion (10pts)

Please clearly state your conclusion and the implication of the result.

1. Conclusion: (1) According to the coefficient, the people who have insomnia will be more likely to be bothered by hair loss. It's reasonable referring to the common sense. (2) According to the coefficient, the probability that women concern about hair loss is larger than men do. (3) From the EDA analysis and model coefficient, we can see that there are relationship between computer\_t(sport\_t, sleep\_t and age) and hair loss. But we need larger sample to determine the precise positive or negative relationship.

2.Implication: In China, hair loss problem has became a popular topic especially among the young people due to their increasing life pressure. Either job or study requires a lot of time facing computer which may results in hair loss. And sedentariness can reduce metabolism. Besides, more and more people suffer from insomnia. I want to clarify the relationship between these phenomenons and hair loss to alert everyone and promote a healthy lifestyle.

### Limitations and future opportunity. (10pts)

Please list concerns about your analysis. Also, please state how you might go about fixing the problem in your future study.

1. Concerns: (1) The data is not large enough with only 56 observations so that it's not persuasive with certain missing value in certain groups. For example, There is only one respondent from group 2 of computer\_t

having concern about hair loss. But her hair loss is mostly related to the poor quality hair dye or perm. After removing such a disturb, there is no respondent from group 2 of computer\_t having concern about hair loss. It's not reasonable and persuasive.

(2) The survey is mainly issued in my Wechat where most of the people are 18-25 or more than 40 years old so the sample is not random enough. (3) The judge of hair loss or not is based on the subjective consciousness of the respondents which may lead to measurement error. (4) The LOO cross validation may be not proper for multilevel model. There is a validation method called leave-one-group-out which will be better for multilevel model.

2.Possible fixing solutions:(1) Take the survey in more general platform which can ensure the randomness. And find more respondents to do the survey. (2) Clarify the evaluation about hair loss or not with more objective and scientific criterion. For example, I can ask the professional doctor for help to set the criterion. (3) There may be interaction among computer\_t, sleep\_t and sport\_t, I should study if the interaction exists or not for fitting model more precisely. (4) I think I should simplify the model in further study.

### Comments or questions

If you have any comments or questions, please write them here.

Question: (1) Is there a good way to deal with the overlapping of factor baseline and intercept if the predictors have more than one index variables? (2) How to properly choose the function for power analysis?