Assignment 06

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library(nlme)  
library(lmerTest)  
library(ggplot2)

mydata <- read.csv("../data/mydata.csv")  
# removing NAs  
mydata <- mydata[!is.na(mydata$insomnia\_severity), ]  
# convert the randomization variable to factor  
mydata$randomization <- factor(mydata$randomization)

## (1) Select a variable in your data for modeling over time. (1 variable, at least 3 occasions). Prepare a person-period (i.e., multiple records per person, “long”) data set for use. Use the same variable and data as Assignment 5.

## (2) Select a time-varying predictor of interest (categorical or continuous)

I will select Anxiety scores as the time-varying predictor.

## (3) Determine how to best model the time-varying predictor and run the analysis. Consider the following in the modeling process:

### a. Is time properly scaled?

### b. How does the predictor affect the DV as specified by your model? Is your model consistent with theory?

### c. Do you need to center your time-varying predictor? How does centering affect your results?

## (4) Write out the equations of your final model

## (5) Make a table for your final model as would appear in a paper

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Main Effects |  | *Est* | *SE* | *p <* |
| Model for the Means | | | | |
|  | Intercept | 27.10 | 1.26 | 0.001 |
|  | Linear time slope | -15.42 | 1.15 | 0.001 |
|  | Quadratic time slope | 2.95 | 0.27 | 0.001 |
|  | Difference in intercept for CBT vs. ACT | 0.11 | 0.83 | 0.90 |
|  | Difference in intercept for Wait list vs. ACT | -1.77 | 0.83 | 0.03 |
|  | Linear slope of PM Anxiety | 0.45 | 0.06 | 0.001 |
|  | Linear slope of WP Anxiety | 0.43 | 0.07 | 0.001 |
|  | Difference in linear slope for CBT vs. ACT | -0.67 | 0.41 | 0.10 |
|  | Difference in linear slope for WL vs. ACT | 2.30 | 0.39 | 0.001 |
| Model for the Variance | | | | |
| Var() | Intercept variance | 2.987 | 1.73 |  |
| Var() | Linear slope variance | 0.488 | 0.70 |  |
| Var() | Residual variance | 9.280 | 3.05 |  |
| ML model fit | | | | |
| AIC |  | 3450 |  |  |
| BIC |  | 3507 |  |  |
| LL |  | -1712 |  |  |

## (6) Write a few sentences reporting the results

The results indicate a significant quadratic change in insomnia severity over time for the ACT reference group, with an initial significant decrease that lessens over time ( = -15.42, *p* < .001; = 2.95, *p* < .001). Compared ACT group, Wait list had significantly lower baseline insomnia severity ( = -1.77 points, *p* = .033) and experienced a significantly shallower linear decrease in insomnia over time ( = 2.30, *p* < .001). Both higher person-mean anxiety ( = 0.45, *p* < .001) and greater within-person deviations in anxiety ( = 0.43, *p* < .001) were significantly associated with increased insomnia severity.

## (7) Include the code you used to complete the assignment.

## Mean-centering anxiety so now an axiety score of 0 means an average score  
mydata$anxiety\_c <- c(scale(mydata$anxiety, scale = FALSE))  
  
## Separating the time-varying predictor into person means and within-person deviations  
mydata2 <- mydata |>   
 dplyr::with\_groups(record\_id, dplyr::mutate, PM\_anxiety = mean(anxiety)) |>   
 dplyr::mutate(PMC\_anxiety = PM\_anxiety - mean(PM\_anxiety),  
 WP\_anxiety = anxiety - PM\_anxiety)

## Building off from the best model of Assignment 5, I will start adding   
## the fixed effects of PMC and WP anxiety  
m1 <- lmer(insomnia\_severity ~ 1 + redcap\_event\_name + I(redcap\_event\_name^2) +  
 redcap\_event\_name\*randomization + PM\_anxiety + WP\_anxiety +  
 (1+ redcap\_event\_name |record\_id),   
 REML=FALSE, data=mydata2)  
  
## No more random effects can be added to the model due to sample size restrictions  
## So I will test models where the time-varying predictor interacts with  
## the time-invariant predictor of randomization  
  
m2 <- lmer(insomnia\_severity ~ 1 + redcap\_event\_name +   
 I(redcap\_event\_name^2) + redcap\_event\_name\*randomization +   
 PM\_anxiety\*randomization + WP\_anxiety\*randomization +  
 (1+ redcap\_event\_name|record\_id),   
 REML=FALSE, data=mydata2)  
anova(m1, m2)

## Data: mydata2  
## Models:  
## m1: insomnia\_severity ~ 1 + redcap\_event\_name + I(redcap\_event\_name^2) + redcap\_event\_name \* randomization + PM\_anxiety + WP\_anxiety + (1 + redcap\_event\_name | record\_id)  
## m2: insomnia\_severity ~ 1 + redcap\_event\_name + I(redcap\_event\_name^2) + redcap\_event\_name \* randomization + PM\_anxiety \* randomization + WP\_anxiety \* randomization + (1 + redcap\_event\_name | record\_id)  
## npar AIC BIC logLik deviance Chisq Df Pr(>Chisq)  
## m1 13 3450.1 3507.7 -1712.1 3424.1   
## m2 17 3451.3 3526.5 -1708.7 3417.3 6.8527 4 0.1439

## Since model 2 doesn't fit significantly better than model 1, I will stick  
## with the more parsimonious model