Chapter 2: Mixed-Effects Models for Factorial Designs

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For these examples, we are going to work with a fictional data that that has two fully nested (i.e., between-subjects) and two fully crossed (i.e., within-subject) factors. We have two hypothetical groups of older adults (OA, >65 y) and younger adults (YA, <35 y). Within each of those groups, half of the participants were in the control group (C) and half were in the treatment group (T). Each participant was also measured at three different times (1 to 3) in three different conditions (A, B, and C).

First, we will open the relevant R packages that we will use and then we will download the data from the web. (If you don’t have these packages installed, you will need install the packages before running the library() function.) Once the data are downloaded we can use the head() function to view the first ten rows of the data.

library(tidyverse); library(RCurl); library(ez); library(lme4); library(lmerTest)

## Warning: package 'ggplot2' was built under R version 4.0.5

## Warning: package 'dplyr' was built under R version 4.0.5

## Warning: package 'RCurl' was built under R version 4.0.4

## Warning: package 'lme4' was built under R version 4.0.5

## Warning: package 'lmerTest' was built under R version 4.0.5

DATA <- read.csv("https://raw.githubusercontent.com/keithlohse/mixed\_effects\_models/master/data\_example.csv")

head(DATA, 10)

## subID group age\_group condition time speed  
## 1 s1 CG OA A 1 0.80  
## 2 s1 CG OA A 2 0.65  
## 3 s1 CG OA A 3 0.63  
## 4 s1 CG OA A 4 0.75  
## 5 s1 CG OA B 1 1.22  
## 6 s1 CG OA B 2 0.78  
## 7 s1 CG OA B 3 0.66  
## 8 s1 CG OA B 4 0.71  
## 9 s1 CG OA C 1 0.97  
## 10 s1 CG OA C 2 0.77

Because we will want to ignore each of the within-subject variables at different times, we will want to average across trials to create a data set with one observation per condition (*data\_COND*), and we will want to average across conditions to create a data set with one observation at each time (*data\_TIME*).

Averaging across time, here are the first ten rows of *data\_COND*.

data\_COND <- aggregate(speed ~ subID + condition + age\_group + group, data=DATA, FUN=mean)  
data\_COND <- data\_COND %>% arrange(subID, age\_group, group, condition)  
head(data\_COND, 10)

## subID condition age\_group group speed  
## 1 s1 A OA CG 0.7075  
## 2 s1 B OA CG 0.8425  
## 3 s1 C OA CG 0.7700  
## 4 s10 A OA CG 0.6100  
## 5 s10 B OA CG 0.8075  
## 6 s10 C OA CG 0.6550  
## 7 s11 A YA CG 1.0500  
## 8 s11 B YA CG 1.0925  
## 9 s11 C YA CG 1.0350  
## 10 s12 A YA CG 0.9675

Averaging across condiitons, here are the first ten rows of data\_TIME.

data\_TIME <- aggregate(speed ~ subID + time + age\_group + group, data=DATA, FUN=mean)  
data\_TIME <- data\_TIME %>% arrange(subID, age\_group, group, time)  
head(data\_TIME)

## subID time age\_group group speed  
## 1 s1 1 OA CG 0.9966667  
## 2 s1 2 OA CG 0.7333333  
## 3 s1 3 OA CG 0.6900000  
## 4 s1 4 OA CG 0.6733333  
## 5 s10 1 OA CG 0.9133333  
## 6 s10 2 OA CG 0.6800000

With these data in place, we can now test all of our different models. We are going to explore the appropriate mixed-effects regression models for these different situations:

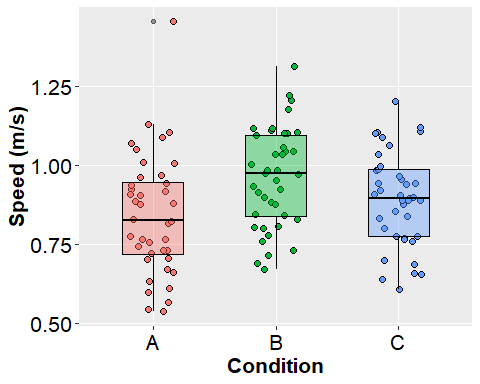
1. **One-Way Repeated Measures ANOVA**
   * When we have a single crossed factor (i.e., one within-subjects factor) in our mixed-ffects model.
2. **Two-Way Repeated Measures ANOVA**
   * When we have mutilple crossed factors (i.e., two within-subjects factors) in our mixed-ffects model.
3. **Mixed-Factorial ANOVA with a Single Within-Subjects Factor**
   * When we have a single crossed factor (i.e., one within-subjects factor) and multiple nested factors (i.e., between-subjects factors) in our mixed-ffects model.
4. **Mixed-Factorial ANOVA with Multiple Within-Subjects Factors**
   * When we have multiple crossed factors (i.e., two within-subjects factor) and multiple nested factors (i.e., between-subjects factors) in our mixed-ffects model.

# 1. One-Way Repeated Measures ANOVA

## (A Single Crossed Factor)

For this example, we will focus on only the effect of condition, so we will use the data\_COND dataset to average across different trials. First, let’s plot the data to get a better sense of what the data look like.

ggplot(data\_COND, aes(x = condition, y = speed)) +  
 geom\_point(aes(fill=condition), pch=21, size=2,  
 position=position\_jitter(w=0.2, h=0))+  
 geom\_boxplot(aes(fill=condition), col="black",   
 alpha=0.4, width=0.5)+  
 scale\_x\_discrete(name = "Condition") +  
 scale\_y\_continuous(name = "Speed (m/s)") +  
 theme(axis.text=element\_text(size=16, color="black"),   
 axis.title=element\_text(size=16, face="bold"),  
 plot.title=element\_text(size=16, face="bold", hjust=0.5),  
 panel.grid.minor = element\_blank(),  
 strip.text = element\_text(size=16, face="bold"),  
 legend.position = "none")



## 1.1. As an ANOVA…

To implement a simple one-way repeated measures ANOVA, we have a few options. We could directly code our ANOVA using the aov() function in R:

summary(aov(speed ~ condition + Error(subID/condition), data=data\_COND))

##   
## Error: subID  
## Df Sum Sq Mean Sq F value Pr(>F)  
## Residuals 39 2.751 0.07054   
##   
## Error: subID:condition  
## Df Sum Sq Mean Sq F value Pr(>F)   
## condition 2 0.2820 0.14098 24.46 5.67e-09 \*\*\*  
## Residuals 78 0.4496 0.00576   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

Or we can use the ezANOVA() function from the “ez” package.

ezANOVA(data = data\_COND,   
 dv = .(speed),  
 wid = .(subID),  
 within = .(condition)  
)

## Warning: Converting "subID" to factor for ANOVA.

## Warning: Converting "condition" to factor for ANOVA.

## $ANOVA  
## Effect DFn DFd F p p<.05 ges  
## 2 condition 2 78 24.46039 5.674295e-09 \* 0.08095761  
##   
## $`Mauchly's Test for Sphericity`  
## Effect W p p<.05  
## 2 condition 0.8955986 0.1230706   
##   
## $`Sphericity Corrections`  
## Effect GGe p[GG] p[GG]<.05 HFe p[HF] p[HF]<.05  
## 2 condition 0.9054678 2.494269e-08 \* 0.947018 1.300658e-08 \*

Although these two different functions present the results in slightly different ways, note that the f-values for the two different omnibus tests match. By either method, the f-observed for the main-effect of condition is F(2,78) = 24.46, p < 0.001.

If you are familiar with issues of contrast versus treatment coding, Type I versus Type III Sums of Squared Errors, and colinearity, then directly controlling your own ANOVA using base R is probably a safe bet. If you are not familiar with those terms/issues, then the ezANOVA code is probably the best solution for a quick fix, but I would strongly encourage you to develop a more detailed understanding of general-linear models before jumping into mixed-effect models.

Specifically, by default the aov() function provides a test of your statistical model using Type I Sums of Squared Errors, whereas the ezANOVA() function provides a test of your statistical model using Type III Sums of Squared Errors. In a completely orthogonal design where all factors are statistically independent of each other (i.e., there is no colinearity), the Type I and Type III Sums of Squared Errors will agree. By default, R also uses treatment coding (or “dummy” coding) for categorical factors rather than orthogonal constrast codes. The omnibus F-tests that we see in the ANOVA output will be the same regardless of the types of codes used, but if we dig into individual regression coefficients, it is important to remember how these variables were coded so that we can interpret them correctly.

## 1.2. One-way RM ANOVA as a mixed-effect model…

Because we have a single within-subject factor, we will need to add a random-effect of subject to account for individual differences between subjects. By partitioning the between-subjects variance out of our model, we can fairly test the effect of condition, because our residuals will now be independent of each other.

# First we will define our model  
mod1 <- lmer(speed ~   
 # Fixed Effects:  
 condition +   
 # Random Effects:   
 (1|subID),   
 # Define the data:   
 data=data\_COND, REML = TRUE)  
  
# We can then get the ANOVA results for our model:  
anova(mod1)

## Type III Analysis of Variance Table with Satterthwaite's method  
## Sum Sq Mean Sq NumDF DenDF F value Pr(>F)   
## condition 0.28196 0.14098 2 78 24.46 5.674e-09 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

Most critically, note that the F-value, F(2,78) = 24.46, p < 0.001 is identical in both the RM ANOVA and in the mixed-effects regression model.

If we want to delve deeper into our model, we can also use the summary() function to get more information about model fit statistics, parameter estimates, random-effects and residuals.

summary(mod1)

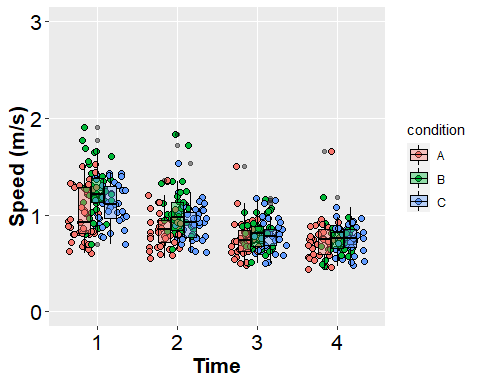
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [  
## lmerModLmerTest]  
## Formula: speed ~ condition + (1 | subID)  
## Data: data\_COND  
##   
## REML criterion at convergence: -162.5  
##   
## Scaled residuals:   
## Min 1Q Median 3Q Max   
## -2.5766 -0.3736 -0.0165 0.3682 3.8369   
##   
## Random effects:  
## Groups Name Variance Std.Dev.  
## subID (Intercept) 0.021594 0.14695   
## Residual 0.005764 0.07592   
## Number of obs: 120, groups: subID, 40  
##   
## Fixed effects:  
## Estimate Std. Error df t value Pr(>|t|)   
## (Intercept) 0.84250 0.02615 52.09109 32.215 <2e-16 \*\*\*  
## conditionB 0.11831 0.01698 78.00000 6.970 9e-10 \*\*\*  
## conditionC 0.05050 0.01698 78.00000 2.975 0.0039 \*\*   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Correlation of Fixed Effects:  
## (Intr) cndtnB  
## conditionB -0.325   
## conditionC -0.325 0.500

# 2. Two-Way Repeated Measures ANOVA

## (Multiple Crossed Factors)

For this example, we will be analyzing both Time and Condition, so we will use our full data frame, *DATA*. First, let’s plot the data to get a better sense of what our data look like.

DATA$time <- factor(DATA$time)  
  
ggplot(DATA, aes(x = time, y = speed)) +  
 geom\_point(aes(fill=condition), pch=21, size=2,  
 position=position\_jitterdodge(dodge.width = 0.5))+  
 geom\_boxplot(aes(fill=condition), col="black",   
 alpha=0.4, width=0.5)+  
 scale\_x\_discrete(name = "Time") +  
 scale\_y\_continuous(name = "Speed (m/s)", limits = c(0,3)) +  
 theme(axis.text=element\_text(size=16, color="black"),   
 axis.title=element\_text(size=16, face="bold"),  
 plot.title=element\_text(size=16, face="bold", hjust=0.5),  
 panel.grid.minor = element\_blank(),  
 strip.text = element\_text(size=16, face="bold"),  
 legend.position = "right")



## 2.1. As an ANOVA…

Before we run our models, we want to convert time to a **factor** so that our model is treating time categorically rather than continuously. (In later modules, we will discuss how to mix continuous and categorical factors.) Additionally, remember that we are now using our larger data set *DATA* rather than our aggregated data set *data\_COND*. To implement a two-way repeated measures ANOVA, we have the same options as before. We can directly code our ANOVA using the aov() function in R:

DATA$time <- factor(DATA$time)  
summary(aov(speed ~ condition\*time + Error(subID/(condition\*time)), data=DATA))

##   
## Error: subID  
## Df Sum Sq Mean Sq F value Pr(>F)  
## Residuals 39 11.01 0.2822   
##   
## Error: subID:condition  
## Df Sum Sq Mean Sq F value Pr(>F)   
## condition 2 1.128 0.5639 24.46 5.67e-09 \*\*\*  
## Residuals 78 1.798 0.0231   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Error: subID:time  
## Df Sum Sq Mean Sq F value Pr(>F)   
## time 3 10.618 3.539 106 <2e-16 \*\*\*  
## Residuals 117 3.909 0.033   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Error: subID:condition:time  
## Df Sum Sq Mean Sq F value Pr(>F)   
## condition:time 6 0.7851 0.13084 13.53 3.59e-13 \*\*\*  
## Residuals 234 2.2626 0.00967   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

Or we can use the ezANOVA() function from the “ez” package.

ezANOVA(data = DATA,   
 dv = .(speed),  
 wid = .(subID),  
 within = .(time, condition)  
)

## Warning: Converting "subID" to factor for ANOVA.

## Warning: Converting "condition" to factor for ANOVA.

## $ANOVA  
## Effect DFn DFd F p p<.05 ges  
## 2 time 3 117 105.95095 3.295544e-33 \* 0.35881815  
## 3 condition 2 78 24.46039 5.674295e-09 \* 0.05610418  
## 4 time:condition 6 234 13.53149 3.588475e-13 \* 0.03973035  
##   
## $`Mauchly's Test for Sphericity`  
## Effect W p p<.05  
## 2 time 0.3262678 5.356910e-08 \*  
## 3 condition 0.8955986 1.230706e-01   
## 4 time:condition 0.2380896 9.170350e-05 \*  
##   
## $`Sphericity Corrections`  
## Effect GGe p[GG] p[GG]<.05 HFe p[HF]  
## 2 time 0.6917461 9.817867e-24 \* 0.7313027 5.956088e-25  
## 3 condition 0.9054678 2.494269e-08 \* 0.9470180 1.300658e-08  
## 4 time:condition 0.6852099 1.068940e-09 \* 0.7760402 1.056951e-10  
## p[HF]<.05  
## 2 \*  
## 3 \*  
## 4 \*

Again, regardless of the coding approach that you use, these two different functions produce the same f-observed for the main-effects of time, F(3,117) = 105.95, p < 0.001, and Condition, F(2, 78) = 24.46, p < 0.001, and the Time x Condition interaction, F(6,234) = 13.53, p < 0.001.

## 2.2. Two-way RM ANOVA as a mixed-effect model…

Because we now have two crossed factors, we need to account not only for the fact that we have multiple observations for each participant, but we have multiple observations coming from other factors. For instance, for the effect of Condition, we actually have Condition effects at Time A, Time B, and Time C. The converse is also true for the effect of Time, we have effects of Time in Condition A, Condition B, and Condition C. Thus, in order to appropriately account for the statistical dependencies in our data, we need to add random-effects of “time:subID” and “condition:subID” to the model.

The colon operator (“:”) means that we are crossing or multiplying these factors. That is, if we have subject ID’s A, B, and C and Trials 1, 2, and 3, then we end up with A1, A2, A3, B1, B2, B3, etc.

For more information on how random-effects are specified and what they mean in R, I recommend looking at the discussion on this webpage: <https://stats.stackexchange.com/questions/228800/crossed-vs-nested-random-effects-how-do-they-differ-and-how-are-they-specified>

# First we will define our model  
mod1 <- lmer(speed ~   
 # Fixed Effects:  
 time\*condition +   
 # Random Effects  
 (1|subID)+ (1|time:subID) + (1|condition:subID),   
 # Define your data,   
 data=DATA, REML=TRUE)  
  
# We can then get the ANOVA results for our model:  
anova(mod1)

## Type III Analysis of Variance Table with Satterthwaite's method  
## Sum Sq Mean Sq NumDF DenDF F value Pr(>F)   
## time 3.07345 1.02448 3 117 105.951 < 2.2e-16 \*\*\*  
## condition 0.47304 0.23652 2 78 24.460 5.674e-09 \*\*\*  
## time:condition 0.78505 0.13084 6 234 13.531 3.588e-13 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

Again, for our purposes, the critical thing to note is that the F-values for the main-effects and interactions are the same between our RM ANOVAs and the mixed-effects model. Without delving into the mathematical details, this is a good demonstration that with the appropriate random-effects our regression model is analogous to the ANOVA. This allows us to capitalize on the benefits of mixed-effects regression for designs that we would normally analyze using factorial ANOVA.

If we want to delve deeper into our model, we can also use the summary() function to get more information about model fit statistics, parameter estimates, random-effects and residuals.

summary(mod1)

## Linear mixed model fit by REML. t-tests use Satterthwaite's method [  
## lmerModLmerTest]  
## Formula: speed ~ time \* condition + (1 | subID) + (1 | time:subID) + (1 |   
## condition:subID)  
## Data: DATA  
##   
## REML criterion at convergence: -454.2  
##   
## Scaled residuals:   
## Min 1Q Median 3Q Max   
## -2.9509 -0.4451 -0.0673 0.3844 3.2827   
##   
## Random effects:  
## Groups Name Variance Std.Dev.  
## time:subID (Intercept) 0.007912 0.08895   
## condition:subID (Intercept) 0.003346 0.05785   
## subID (Intercept) 0.019616 0.14006   
## Residual 0.009669 0.09833   
## Number of obs: 480, groups: time:subID, 160; condition:subID, 120; subID, 40  
##   
## Fixed effects:  
## Estimate Std. Error df t value Pr(>|t|)   
## (Intercept) 1.00975 0.03184 109.12304 31.716 < 2e-16 \*\*\*  
## time2 -0.15300 0.02965 249.81033 -5.160 5.03e-07 \*\*\*  
## time3 -0.25350 0.02965 249.81033 -8.550 1.25e-15 \*\*\*  
## time4 -0.26250 0.02965 249.81033 -8.853 < 2e-16 \*\*\*  
## conditionB 0.24625 0.02551 260.37317 9.653 < 2e-16 \*\*\*  
## conditionC 0.10125 0.02551 260.37317 3.969 9.34e-05 \*\*\*  
## time2:conditionB -0.07025 0.03110 234.00008 -2.259 0.02479 \*   
## time3:conditionB -0.19800 0.03110 234.00008 -6.367 1.01e-09 \*\*\*  
## time4:conditionB -0.24350 0.03110 234.00008 -7.831 1.68e-13 \*\*\*  
## time2:conditionC -0.03825 0.03110 234.00008 -1.230 0.21990   
## time3:conditionC -0.06425 0.03110 234.00008 -2.066 0.03991 \*   
## time4:conditionC -0.10050 0.03110 234.00008 -3.232 0.00141 \*\*   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Correlation of Fixed Effects:  
## (Intr) time2 time3 time4 cndtnB cndtnC tm2:cB tm3:cB tm4:cB  
## time2 -0.466   
## time3 -0.466 0.500   
## time4 -0.466 0.500 0.500   
## conditionB -0.401 0.320 0.320 0.320   
## conditionC -0.401 0.320 0.320 0.320 0.500   
## tim2:cndtnB 0.244 -0.524 -0.262 -0.262 -0.609 -0.305   
## tim3:cndtnB 0.244 -0.262 -0.524 -0.262 -0.609 -0.305 0.500   
## tim4:cndtnB 0.244 -0.262 -0.262 -0.524 -0.609 -0.305 0.500 0.500   
## tim2:cndtnC 0.244 -0.524 -0.262 -0.262 -0.305 -0.609 0.500 0.250 0.250  
## tim3:cndtnC 0.244 -0.262 -0.524 -0.262 -0.305 -0.609 0.250 0.500 0.250  
## tim4:cndtnC 0.244 -0.262 -0.262 -0.524 -0.305 -0.609 0.250 0.250 0.500  
## tm2:cC tm3:cC  
## time2   
## time3   
## time4   
## conditionB   
## conditionC   
## tim2:cndtnB   
## tim3:cndtnB   
## tim4:cndtnB   
## tim2:cndtnC   
## tim3:cndtnC 0.500   
## tim4:cndtnC 0.500 0.500

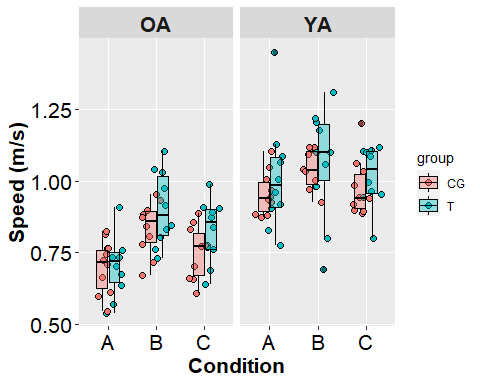
# 3. Mixed-Factorial ANOVA with One Crossed Factor

## (Split-Plot Design)

For this example, we will now consider both of our between-subject factors of age and treatment, as well as the within-subject factor of condition. Do to this, we will average over the different times (1, 2, and 3) to get one observation in each condition. This design is sometimes referred as a “mixed-factorial” design, because we have a mix of between-subjects and within-subject factors. Depending on your background, you might be more familiar with this as a “split plot” design. Split plot refers to the fact that some plots are assigned to different levels of Factor A (e.g., Treatment versus Control), but within each plot there is a second level of randomization to different levels of Factor B (e.g., Conditions A, B, or C). Both terms describe the same thing but differ in their unit of analysis. In pscyhology, a single person is usually the experimental unit (hence “within-subject” variables) whereas in agronomy or biology a physical area might be the unit of analysis (hence “split-plot” variables). The more general way to talk about these terms is as nested- or crossed-factors. For fully nested factors, an experimental unit is represented in only one of the factors (e.g., a person can only be in the treatment group or the control group). For fully crossed factors, an experimental unit is represented at all levels of the factor (e.g., e.g., a person is tested in conditions A, B, and C).

In our example, Treatment and Age-Group are nested factors, because each person is represented at only one level of each factor. However, Condition is a crossed factor, because each person is represented at all levels of Condition. We can see this more clearly if we plot all of our data.

ggplot(data\_COND, aes(x = condition, y = speed)) +  
 geom\_point(aes(fill=group), pch=21, size=2,  
 position=position\_jitterdodge(dodge.width = 0.5))+  
 geom\_boxplot(aes(fill=group), col="black",  
 alpha=0.4, width=0.5)+  
 facet\_wrap(~age\_group)+  
 scale\_x\_discrete(name = "Condition") +  
 scale\_y\_continuous(name = "Speed (m/s)") +  
 theme(axis.text=element\_text(size=16, color="black"),   
 axis.title=element\_text(size=16, face="bold"),  
 plot.title=element\_text(size=16, face="bold", hjust=0.5),  
 panel.grid.minor = element\_blank(),  
 strip.text = element\_text(size=16, face="bold"),  
 legend.position = "right")



## 3.1. As an ANOVA…

For this mixed factorial ANOVA, we have one factor of Condition that varies within subjects, but we have two factors (Age Group and Treatment Group) that vary between subjects. As before, we can directly code this into our analysis of variance using the aov() function or using the ezANOVA() function from the “ez” package.

summary(aov(speed ~ age\_group\*group\*condition + Error(subID/condition), data=data\_COND))

##   
## Error: subID  
## Df Sum Sq Mean Sq F value Pr(>F)   
## age\_group 1 1.5238 1.5238 46.962 5.12e-08 \*\*\*  
## group 1 0.0589 0.0589 1.814 0.186   
## age\_group:group 1 0.0005 0.0005 0.014 0.907   
## Residuals 36 1.1681 0.0324   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Error: subID:condition  
## Df Sum Sq Mean Sq F value Pr(>F)   
## condition 2 0.2820 0.14098 27.107 1.67e-09 \*\*\*  
## age\_group:condition 2 0.0567 0.02834 5.449 0.00626 \*\*   
## group:condition 2 0.0042 0.00211 0.405 0.66837   
## age\_group:group:condition 2 0.0142 0.00711 1.366 0.26155   
## Residuals 72 0.3745 0.00520   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

Or we can use the ezANOVA() function from the “ez” package.

ezANOVA(data = data\_COND,   
 dv = .(speed),  
 wid = .(subID),  
 within = .(condition),  
 between = .(group, age\_group)  
)

## Warning: Converting "subID" to factor for ANOVA.

## Warning: Converting "condition" to factor for ANOVA.

## Warning: Converting "group" to factor for ANOVA.

## Warning: Converting "age\_group" to factor for ANOVA.

## $ANOVA  
## Effect DFn DFd F p p<.05 ges  
## 2 group 1 36 1.81375927 1.864757e-01 0.036750099  
## 3 age\_group 1 36 46.96205340 5.123596e-08 \* 0.496941614  
## 5 condition 2 72 27.10735710 1.674983e-09 \* 0.154535896  
## 4 group:age\_group 1 36 0.01388286 9.068608e-01 0.000291939  
## 6 group:condition 2 72 0.40518292 6.683658e-01 0.002724666  
## 7 age\_group:condition 2 72 5.44874333 6.258652e-03 \* 0.035438340  
## 8 group:age\_group:condition 2 72 1.36642954 2.615486e-01 0.009129587  
##   
## $`Mauchly's Test for Sphericity`  
## Effect W p p<.05  
## 5 condition 0.8796257 0.1059775   
## 6 group:condition 0.8796257 0.1059775   
## 7 age\_group:condition 0.8796257 0.1059775   
## 8 group:age\_group:condition 0.8796257 0.1059775   
##   
## $`Sphericity Corrections`  
## Effect GGe p[GG] p[GG]<.05 HFe  
## 5 condition 0.8925589 1.024946e-08 \* 0.9359868  
## 6 group:condition 0.8925589 6.452953e-01 0.9359868  
## 7 age\_group:condition 0.8925589 8.436500e-03 \* 0.9359868  
## 8 group:age\_group:condition 0.8925589 2.613003e-01 0.9359868  
## p[HF] p[HF]<.05  
## 5 4.926384e-09 \*  
## 6 6.549437e-01   
## 7 7.476211e-03 \*  
## 8 2.614846e-01

The ezANOVA() function provides us with more detail, for instance automatically providing Mauchly’s Test for Sphericity and both the Greenhouse-Geisser and Hyunh-Feldt corrections in the event that the sphericity assumption is violated. Most importantly, the outputs of these two functions agree when we look at the f-statistics for all main-effects and interactions when sphericity is assumed.

## 3.2. Mixed Factorial ANOVA as a mixed-effect model…

For this mixed-factorial design, we need to account for the fact that we have multiple observations coming from each person, so we will add a random-effect of “subID”. After accounting for this statistical dependence in our data, we can now fairly test the effects of Group, Age Group, and Condition with residuals that are independent of each other.

# First we will define our model  
mod1 <- lmer(speed ~   
 # Fixed Effects:  
 group\*age\_group\*condition +   
 # Random Effects  
 (1|subID),   
 # Define your data,   
 data=data\_COND, REML=TRUE)  
  
# We can then get the ANOVA results for our model:  
anova(mod1)

## Type III Analysis of Variance Table with Satterthwaite's method  
## Sum Sq Mean Sq NumDF DenDF F value Pr(>F)   
## group 0.009433 0.009433 1 36 1.8138 0.186476   
## age\_group 0.244236 0.244236 1 36 46.9620 5.124e-08 \*\*\*  
## condition 0.281955 0.140978 2 72 27.1074 1.675e-09 \*\*\*  
## group:age\_group 0.000072 0.000072 1 36 0.0139 0.906861   
## group:condition 0.004214 0.002107 2 72 0.4052 0.668366   
## age\_group:condition 0.056675 0.028337 2 72 5.4487 0.006259 \*\*   
## group:age\_group:condition 0.014213 0.007106 2 72 1.3664 0.261549   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

If we want to delve deeper into our model, we can also use the summary() function to get more information about model fit statistics, parameter estimates, random-effects and residuals.

summary(mod1)

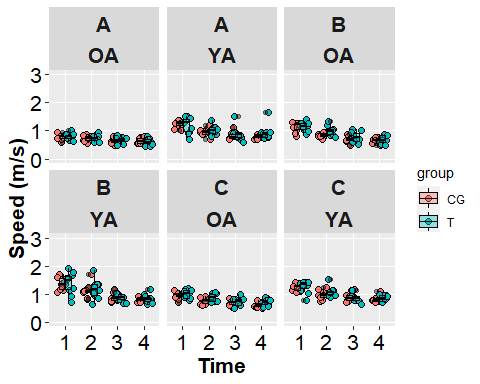
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [  
## lmerModLmerTest]  
## Formula: speed ~ group \* age\_group \* condition + (1 | subID)  
## Data: data\_COND  
##   
## REML criterion at convergence: -167.9  
##   
## Scaled residuals:   
## Min 1Q Median 3Q Max   
## -2.5615 -0.4127 -0.0775 0.4832 3.6041   
##   
## Random effects:  
## Groups Name Variance Std.Dev.  
## subID (Intercept) 0.009082 0.09530   
## Residual 0.005201 0.07212   
## Number of obs: 120, groups: subID, 40  
##   
## Fixed effects:  
## Estimate Std. Error df t value Pr(>|t|)   
## (Intercept) 0.69900 0.03779 59.71156 18.496 < 2e-16 \*\*\*  
## groupT 0.00200 0.05345 59.71156 0.037 0.970   
## age\_groupYA 0.25825 0.05345 59.71156 4.832 9.82e-06 \*\*\*  
## conditionB 0.13625 0.03225 72.00000 4.225 6.91e-05 \*\*\*  
## conditionC 0.05275 0.03225 72.00000 1.636 0.106   
## groupT:age\_groupYA 0.05350 0.07559 59.71156 0.708 0.482   
## groupT:conditionB 0.06650 0.04561 72.00000 1.458 0.149   
## groupT:conditionC 0.07200 0.04561 72.00000 1.579 0.119   
## age\_groupYA:conditionB -0.05375 0.04561 72.00000 -1.178 0.242   
## age\_groupYA:conditionC -0.03325 0.04561 72.00000 -0.729 0.468   
## groupT:age\_groupYA:conditionB -0.09725 0.06450 72.00000 -1.508 0.136   
## groupT:age\_groupYA:conditionC -0.08650 0.06450 72.00000 -1.341 0.184   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Correlation of Fixed Effects:  
## (Intr) groupT ag\_gYA cndtnB cndtnC grT:\_YA grpT:B grpT:C a\_YA:B  
## groupT -0.707   
## age\_groupYA -0.707 0.500   
## conditionB -0.427 0.302 0.302   
## conditionC -0.427 0.302 0.302 0.500   
## grpT:g\_grYA 0.500 -0.707 -0.707 -0.213 -0.213   
## grpT:cndtnB 0.302 -0.427 -0.213 -0.707 -0.354 0.302   
## grpT:cndtnC 0.302 -0.427 -0.213 -0.354 -0.707 0.302 0.500   
## ag\_grpYA:cB 0.302 -0.213 -0.427 -0.707 -0.354 0.302 0.500 0.250   
## ag\_grpYA:cC 0.302 -0.213 -0.427 -0.354 -0.707 0.302 0.250 0.500 0.500  
## grpT:g\_YA:B -0.213 0.302 0.302 0.500 0.250 -0.427 -0.707 -0.354 -0.707  
## grpT:g\_YA:C -0.213 0.302 0.302 0.250 0.500 -0.427 -0.354 -0.707 -0.354  
## a\_YA:C gT:\_YA:B  
## groupT   
## age\_groupYA   
## conditionB   
## conditionC   
## grpT:g\_grYA   
## grpT:cndtnB   
## grpT:cndtnC   
## ag\_grpYA:cB   
## ag\_grpYA:cC   
## grpT:g\_YA:B -0.354   
## grpT:g\_YA:C -0.707 0.500

# 4. Mixed-Factorial ANOVA with Multiple Crossed Factors

## (Multi-Way Split-Plot Design)

Next, we will consider the more complicated example of our fully factorial design with nested factors of Group and Age-Group, and crossed factors of Condition and Time.

DATA$time <- factor(DATA$time)  
  
ggplot(DATA, aes(x = time, y = speed)) +  
 geom\_point(aes(fill=group), size=2, shape=21,  
 position=position\_jitterdodge(dodge.width = 0.5))+  
 geom\_boxplot(aes(fill=group), col="black",   
 alpha=0.4, width=0.5)+  
 facet\_wrap(~condition+age\_group)+  
 scale\_x\_discrete(name = "Time") +  
 scale\_y\_continuous(name = "Speed (m/s)", limits = c(0,3)) +  
 theme(axis.text=element\_text(size=16, color="black"),   
 axis.title=element\_text(size=16, face="bold"),  
 plot.title=element\_text(size=16, face="bold", hjust=0.5),  
 panel.grid.minor = element\_blank(),  
 strip.text = element\_text(size=16, face="bold"),  
 legend.position = "right")



## 4.1. As an ANOVA…

For this mixed factorial ANOVA, we have two factors that vary within subjects, Condition and Time, and we have two factors that vary between subjects, Age Group and treatment Group. As before, we can directly code this into our analysis of variance using the aov() function or using the ezANOVA() function from the “ez” package.

summary(aov(speed ~ age\_group\*group\*condition\*time + Error(subID/(condition\*time)), data=DATA))

##   
## Error: subID  
## Df Sum Sq Mean Sq F value Pr(>F)   
## age\_group 1 6.095 6.095 46.962 5.12e-08 \*\*\*  
## group 1 0.235 0.235 1.814 0.186   
## age\_group:group 1 0.002 0.002 0.014 0.907   
## Residuals 36 4.672 0.130   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Error: subID:condition  
## Df Sum Sq Mean Sq F value Pr(>F)   
## condition 2 1.1278 0.5639 27.107 1.67e-09 \*\*\*  
## age\_group:condition 2 0.2267 0.1133 5.449 0.00626 \*\*   
## group:condition 2 0.0169 0.0084 0.405 0.66837   
## age\_group:group:condition 2 0.0569 0.0284 1.366 0.26155   
## Residuals 72 1.4978 0.0208   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Error: subID:time  
## Df Sum Sq Mean Sq F value Pr(>F)   
## time 3 10.618 3.539 111.342 <2e-16 \*\*\*  
## age\_group:time 3 0.365 0.122 3.832 0.0119 \*   
## group:time 3 0.087 0.029 0.907 0.4401   
## age\_group:group:time 3 0.023 0.008 0.245 0.8649   
## Residuals 108 3.433 0.032   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Error: subID:condition:time  
## Df Sum Sq Mean Sq F value Pr(>F)   
## condition:time 6 0.7851 0.13084 13.844 2.65e-13 \*\*\*  
## age\_group:condition:time 6 0.0880 0.01467 1.553 0.162   
## group:condition:time 6 0.0653 0.01089 1.152 0.333   
## age\_group:group:condition:time 6 0.0679 0.01131 1.197 0.309   
## Residuals 216 2.0414 0.00945   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

ezANOVA(data = DATA,   
 dv = .(speed),  
 wid = .(subID),  
 within = .(condition, time),  
 between = .(group, age\_group)  
)

## Warning: Converting "subID" to factor for ANOVA.

## Warning: Converting "condition" to factor for ANOVA.

## Warning: Converting "group" to factor for ANOVA.

## Warning: Converting "age\_group" to factor for ANOVA.

## $ANOVA  
## Effect DFn DFd F p p<.05  
## 2 group 1 36 1.81375927 1.864757e-01   
## 3 age\_group 1 36 46.96205340 5.123596e-08 \*  
## 5 condition 2 72 27.10735710 1.674983e-09 \*  
## 9 time 3 108 111.34181694 6.498550e-33 \*  
## 4 group:age\_group 1 36 0.01388286 9.068608e-01   
## 6 group:condition 2 72 0.40518292 6.683658e-01   
## 7 age\_group:condition 2 72 5.44874333 6.258652e-03 \*  
## 10 group:time 3 108 0.90734936 4.401113e-01   
## 11 age\_group:time 3 108 3.83225811 1.186162e-02 \*  
## 13 condition:time 6 216 13.84433326 2.654458e-13 \*  
## 8 group:age\_group:condition 2 72 1.36642954 2.615486e-01   
## 12 group:age\_group:time 3 108 0.24474218 8.649151e-01   
## 14 group:condition:time 6 216 1.15186298 3.334606e-01   
## 15 age\_group:condition:time 6 216 1.55269051 1.623873e-01   
## 16 group:age\_group:condition:time 6 216 1.19712599 3.089058e-01   
## ges  
## 2 0.0198150733  
## 3 0.3435846877  
## 5 0.0882988091  
## 9 0.4769469528  
## 4 0.0001547105  
## 6 0.0014455663  
## 7 0.0190958101  
## 10 0.0073760749  
## 11 0.0304298646  
## 13 0.0631577772  
## 8 0.0048583332  
## 12 0.0020003466  
## 14 0.0055777621  
## 15 0.0075041573  
## 16 0.0057956726  
##   
## $`Mauchly's Test for Sphericity`  
## Effect W p p<.05  
## 5 condition 0.8796257 1.059775e-01   
## 6 group:condition 0.8796257 1.059775e-01   
## 7 age\_group:condition 0.8796257 1.059775e-01   
## 8 group:age\_group:condition 0.8796257 1.059775e-01   
## 9 time 0.3207606 1.943049e-07 \*  
## 10 group:time 0.3207606 1.943049e-07 \*  
## 11 age\_group:time 0.3207606 1.943049e-07 \*  
## 12 group:age\_group:time 0.3207606 1.943049e-07 \*  
## 13 condition:time 0.1870732 2.496563e-05 \*  
## 14 group:condition:time 0.1870732 2.496563e-05 \*  
## 15 age\_group:condition:time 0.1870732 2.496563e-05 \*  
## 16 group:age\_group:condition:time 0.1870732 2.496563e-05 \*  
##   
## $`Sphericity Corrections`  
## Effect GGe p[GG] p[GG]<.05 HFe  
## 5 condition 0.8925589 1.024946e-08 \* 0.9359868  
## 6 group:condition 0.8925589 6.452953e-01 0.9359868  
## 7 age\_group:condition 0.8925589 8.436500e-03 \* 0.9359868  
## 8 group:age\_group:condition 0.8925589 2.613003e-01 0.9359868  
## 9 time 0.6937448 1.384236e-23 \* 0.7371108  
## 10 group:time 0.6937448 4.114075e-01 0.7371108  
## 11 age\_group:time 0.6937448 2.456109e-02 \* 0.7371108  
## 12 group:age\_group:time 0.6937448 7.921234e-01 0.7371108  
## 13 condition:time 0.6368150 3.038071e-09 \* 0.7218603  
## 14 group:condition:time 0.6368150 3.344592e-01 0.7218603  
## 15 age\_group:condition:time 0.6368150 1.928505e-01 0.7218603  
## 16 group:age\_group:condition:time 0.6368150 3.148862e-01 0.7218603  
## p[HF] p[HF]<.05  
## 5 4.926384e-09 \*  
## 6 6.549437e-01   
## 7 7.476211e-03 \*  
## 8 2.614846e-01   
## 9 6.590443e-25 \*  
## 10 4.163079e-01   
## 11 2.213996e-02 \*  
## 12 8.049637e-01   
## 13 3.381165e-10 \*  
## 14 3.349906e-01   
## 15 1.853155e-01   
## 16 3.141173e-01

## 4.2. Multi-Way Mixed Factorial ANOVA as a mixed-effect model…

For this mixed-factorial design, we need to account for the fact that we have multiple observations coming from each person, but we also need to acocunt for the fact that we multiple observations for each Condition and at each Time. In order to account for this non-independence in our data, we need to include random-effects of subject, subject:condition, and subject:time. Adding these random-effects to our model will make our mixed-effects model statistically equivalent to the mixed-factorial ANOVAs that we ran above.

# First we will define our model  
mod1 <- lmer(speed ~   
 # Fixed Effects:  
 group\*age\_group\*condition\*time +   
 # Random Effects  
 (1|subID)+(1|condition:subID)+(1|time:subID),   
 # Define your data,   
 data=DATA, REML=TRUE)  
  
# We can then get the ANOVA results for our model:  
anova(mod1)

## Type III Analysis of Variance Table with Satterthwaite's method  
## Sum Sq Mean Sq NumDF DenDF F value Pr(>F)  
## group 0.01714 0.01714 1 36 1.8138 0.186476  
## age\_group 0.44384 0.44384 1 36 46.9621 5.123e-08  
## condition 0.51238 0.25619 2 72 27.1073 1.675e-09  
## time 3.15686 1.05229 3 108 111.3419 < 2.2e-16  
## group:age\_group 0.00013 0.00013 1 36 0.0139 0.906861  
## group:condition 0.00766 0.00383 2 72 0.4052 0.668366  
## age\_group:condition 0.10299 0.05150 2 72 5.4487 0.006259  
## group:time 0.02573 0.00858 3 108 0.9073 0.440111  
## age\_group:time 0.10866 0.03622 3 108 3.8323 0.011862  
## condition:time 0.78505 0.13084 6 216 13.8443 2.654e-13  
## group:age\_group:condition 0.02583 0.01291 2 72 1.3664 0.261549  
## group:age\_group:time 0.00694 0.00231 3 108 0.2447 0.864915  
## group:condition:time 0.06532 0.01089 6 216 1.1519 0.333461  
## age\_group:condition:time 0.08805 0.01467 6 216 1.5527 0.162387  
## group:age\_group:condition:time 0.06788 0.01131 6 216 1.1971 0.308906  
##   
## group   
## age\_group \*\*\*  
## condition \*\*\*  
## time \*\*\*  
## group:age\_group   
## group:condition   
## age\_group:condition \*\*   
## group:time   
## age\_group:time \*   
## condition:time \*\*\*  
## group:age\_group:condition   
## group:age\_group:time   
## group:condition:time   
## age\_group:condition:time   
## group:age\_group:condition:time   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

If we want to delve deeper into our model, we can also use the summary() function to get more information about model fit statistics, parameter estimates, random-effects and residuals.

summary(mod1)

## Linear mixed model fit by REML. t-tests use Satterthwaite's method [  
## lmerModLmerTest]  
## Formula: speed ~ group \* age\_group \* condition \* time + (1 | subID) +   
## (1 | condition:subID) + (1 | time:subID)  
## Data: DATA  
##   
## REML criterion at convergence: -395.2  
##   
## Scaled residuals:   
## Min 1Q Median 3Q Max   
## -2.9148 -0.3719 -0.0487 0.3383 3.1627   
##   
## Random effects:  
## Groups Name Variance Std.Dev.  
## time:subID (Intercept) 0.007446 0.08629   
## condition:subID (Intercept) 0.002838 0.05327   
## subID (Intercept) 0.007221 0.08498   
## Residual 0.009451 0.09722   
## Number of obs: 480, groups: time:subID, 160; condition:subID, 120; subID, 40  
##   
## Fixed effects:  
## Estimate Std. Error df t value  
## (Intercept) 0.78500 0.05192 177.02101 15.120  
## groupT 0.01800 0.07343 177.02101 0.245  
## age\_groupYA 0.46200 0.07343 177.02101 6.292  
## conditionB 0.35000 0.04958 248.27611 7.060  
## conditionC 0.16100 0.04958 248.27611 3.248  
## time2 -0.05900 0.05813 233.36362 -1.015  
## time3 -0.14000 0.05813 233.36362 -2.408  
## time4 -0.14500 0.05813 233.36362 -2.494  
## groupT:age\_groupYA -0.06100 0.10384 177.02101 -0.587  
## groupT:conditionB -0.00300 0.07011 248.27611 -0.043  
## groupT:conditionC 0.03300 0.07011 248.27611 0.471  
## age\_groupYA:conditionB -0.23900 0.07011 248.27611 -3.409  
## age\_groupYA:conditionC -0.16800 0.07011 248.27611 -2.396  
## groupT:time2 -0.01600 0.08221 233.36362 -0.195  
## groupT:time3 0.00100 0.08221 233.36362 0.012  
## groupT:time4 -0.04900 0.08221 233.36362 -0.596  
## age\_groupYA:time2 -0.23900 0.08221 233.36362 -2.907  
## age\_groupYA:time3 -0.28300 0.08221 233.36362 -3.442  
## age\_groupYA:time4 -0.29300 0.08221 233.36362 -3.564  
## conditionB:time2 -0.23200 0.06148 216.00000 -3.773  
## conditionC:time2 -0.12700 0.06148 216.00000 -2.066  
## conditionB:time3 -0.29400 0.06148 216.00000 -4.782  
## conditionC:time3 -0.11200 0.06148 216.00000 -1.822  
## conditionB:time4 -0.32900 0.06148 216.00000 -5.351  
## conditionC:time4 -0.19400 0.06148 216.00000 -3.155  
## groupT:age\_groupYA:conditionB 0.06900 0.09915 248.27611 0.696  
## groupT:age\_groupYA:conditionC 0.03100 0.09915 248.27611 0.313  
## groupT:age\_groupYA:time2 0.13400 0.11627 233.36362 1.153  
## groupT:age\_groupYA:time3 0.11000 0.11627 233.36362 0.946  
## groupT:age\_groupYA:time4 0.21400 0.11627 233.36362 1.841  
## groupT:conditionB:time2 0.15500 0.08695 216.00000 1.783  
## groupT:conditionC:time2 0.07500 0.08695 216.00000 0.863  
## groupT:conditionB:time3 0.06100 0.08695 216.00000 0.702  
## groupT:conditionC:time3 -0.02200 0.08695 216.00000 -0.253  
## groupT:conditionB:time4 0.06200 0.08695 216.00000 0.713  
## groupT:conditionC:time4 0.10300 0.08695 216.00000 1.185  
## age\_groupYA:conditionB:time2 0.29500 0.08695 216.00000 3.393  
## age\_groupYA:conditionC:time2 0.15000 0.08695 216.00000 1.725  
## age\_groupYA:conditionB:time3 0.22400 0.08695 216.00000 2.576  
## age\_groupYA:conditionC:time3 0.19600 0.08695 216.00000 2.254  
## age\_groupYA:conditionB:time4 0.22200 0.08695 216.00000 2.553  
## age\_groupYA:conditionC:time4 0.19300 0.08695 216.00000 2.220  
## groupT:age\_groupYA:conditionB:time2 -0.25300 0.12297 216.00000 -2.057  
## groupT:age\_groupYA:conditionC:time2 -0.09500 0.12297 216.00000 -0.773  
## groupT:age\_groupYA:conditionB:time3 -0.18600 0.12297 216.00000 -1.513  
## groupT:age\_groupYA:conditionC:time3 -0.15700 0.12297 216.00000 -1.277  
## groupT:age\_groupYA:conditionB:time4 -0.22600 0.12297 216.00000 -1.838  
## groupT:age\_groupYA:conditionC:time4 -0.21800 0.12297 216.00000 -1.773  
## Pr(>|t|)   
## (Intercept) < 2e-16 \*\*\*  
## groupT 0.806625   
## age\_groupYA 2.38e-09 \*\*\*  
## conditionB 1.66e-11 \*\*\*  
## conditionC 0.001325 \*\*   
## time2 0.311196   
## time3 0.016804 \*   
## time4 0.013314 \*   
## groupT:age\_groupYA 0.557648   
## groupT:conditionB 0.965904   
## groupT:conditionC 0.638281   
## age\_groupYA:conditionB 0.000761 \*\*\*  
## age\_groupYA:conditionC 0.017307 \*   
## groupT:time2 0.845861   
## groupT:time3 0.990305   
## groupT:time4 0.551740   
## age\_groupYA:time2 0.003999 \*\*   
## age\_groupYA:time3 0.000683 \*\*\*  
## age\_groupYA:time4 0.000443 \*\*\*  
## conditionB:time2 0.000208 \*\*\*  
## conditionC:time2 0.040064 \*   
## conditionB:time3 3.22e-06 \*\*\*  
## conditionC:time3 0.069900 .   
## conditionB:time4 2.23e-07 \*\*\*  
## conditionC:time4 0.001832 \*\*   
## groupT:age\_groupYA:conditionB 0.487142   
## groupT:age\_groupYA:conditionC 0.754808   
## groupT:age\_groupYA:time2 0.250281   
## groupT:age\_groupYA:time3 0.345071   
## groupT:age\_groupYA:time4 0.066948 .   
## groupT:conditionB:time2 0.076059 .   
## groupT:conditionC:time2 0.389347   
## groupT:conditionB:time3 0.483726   
## groupT:conditionC:time3 0.800500   
## groupT:conditionB:time4 0.476595   
## groupT:conditionC:time4 0.237496   
## age\_groupYA:conditionB:time2 0.000823 \*\*\*  
## age\_groupYA:conditionC:time2 0.085944 .   
## age\_groupYA:conditionB:time3 0.010658 \*   
## age\_groupYA:conditionC:time3 0.025193 \*   
## age\_groupYA:conditionB:time4 0.011366 \*   
## age\_groupYA:conditionC:time4 0.027486 \*   
## groupT:age\_groupYA:conditionB:time2 0.040847 \*   
## groupT:age\_groupYA:conditionC:time2 0.440634   
## groupT:age\_groupYA:conditionB:time3 0.131851   
## groupT:age\_groupYA:conditionC:time3 0.203065   
## groupT:age\_groupYA:conditionB:time4 0.067457 .   
## groupT:age\_groupYA:conditionC:time4 0.077672 .   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

##   
## Correlation matrix not shown by default, as p = 48 > 12.  
## Use print(x, correlation=TRUE) or  
## vcov(x) if you need it