# Research Methods and Statistics with R 3

# Week 4 – ANOVA III: Factorial Designs

## Introduction to the session

In this session, you will continue to practise your statistical and coding skills for yet more types of ANOVAs. Here, you will examine factorial (independent) designs including follow-up contrasts. For the purposes of this session, we will assume that all contrasts are *post-*hoc (meaning they are not planned in advance and must be corrected for multiple comparisons). When constructing your contrasts, be sure to keep in mind the principles regarding orthogonality discussed in Week 3.

In terms of dataset, we are going to yet again examine a simulated dataset based on real work. As before, these data are meant to emulate the kinds of data you might find yourself analysing during your placement year, year abroad, and/or your third year projects.

## Background

An emerging treatment for clinical depression and other mental health conditions is the use of psychedelic and hallucinogenic drugs. While these drugs have shown promising results in terms of treatment outcomes, they are not without their side-effects (including some not-so-fun ones). In particular, psychedelic and hallucinogenic drugs have been shown to have negative effects on general cognition, memory, and executive control.

The dataset you will analyse is (very loosely) based on several recent articles examining the effects of psychedelic and hallucinogenic drugs on cognition. Your goal today will be to evaluate the claims that these drugs have an effect on performance scores in a standard test of working memory: the N-back task.

In the N-back task, a participant is presented with a continuous stream of visual stimuli (e.g., characters, numbers, images, etc.) and must indicate whether the current image matches the image presented “N” images ago. For example, in a two-back condition, the participant must indicate whether the current image matches the stimulus that was presented two stimuli ago. The higher the “N”, the more difficult the task (i.e., a 2-back task is pretty easy, a 4-back task is really hard). Performance can be measured as a function of “Hits” (correct answers), “False Alarms” (incorrectly indicating a match), “Misses” (incorrectly missing a match), “Correct Rejections” (correctly not indicating a match), and various other signal detection measures. For this session, we will use the **d-prime** measure from each participant, which is calculated using the following formula:

In our hypothetical experiment, participants have been divided into **twelve different groups** based on a) their clinical condition (no depression, sub-clinical depression, clinically-depressed); and b) the drug they were given prior to completing the N-back task (placebo, psilocybin, dextromethorphan, fluoxetine). Each group contains 20 participants. The task they performed was a **three-back task**, with a total of 20 possible targets and 30 distractors. You will be provided with a dataframe containing the number of hits, misses, false alarms, and correct rejections for a 3-back task for each of the 80 participants. You will need to:

1. Calculate the d-prime for each participant based on their performance measures
2. Visualise the data using a figure geometry (e.g., boxplot, line graph, etc.) appropriate for the experimental design
3. Conduct an appropriate statistical analysis including any follow-up tests that you believe are appropriate.

## Learning Outcomes

By the end of this session, you will be able to:

1. Process behavioural data (calculate d-prime)
2. Apply factorial ANOVAs to behavioural data using R
3. To analyse, interpret, and summarise behavioural data

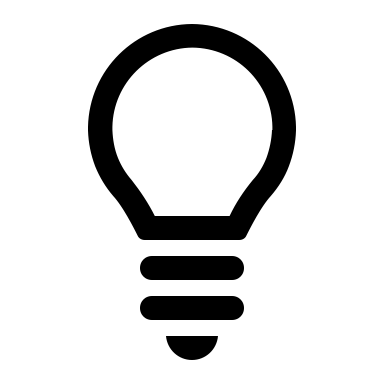
## Procedure

1. Start a new R script. Be sure to include whatever naming and commenting conventions you feel are appropriate.
2. Read through the above information and be sure that you can answer the following questions (note your answers in the comment section of your R-script):
   1. What is your research question?
   2. What is your design?
   3. How many sets of nulls/alternative hypotheses should you have? What are your nulls/alternatives?
   4. What contrasts (if any) do you think might be necessary to further understand your data?
3. Generate a **contrast object** (hint: use the approach described in the lecture material). Remember, the key is to minimise the number of contrasts to avoid artificially inflating your family-wise error. Based on the description above, what do you suppose are some reasonable contrasts to conduct? (Note: there are several right answers here).
4. Download the simulated data from KEATS and load the file into your workspace.
5. Inspect your data using an appropriate tool, like dplyr::glimpse(), to make sure they have imported appropriately. Pay particular attention to the variable types (i.e., numeric, factor, character, etc.).
6. Before calculating descriptive statistics for each group, you must first calculate the d-prime for each participant. You have been given the number of hits, false alarms, etc. for each participant. You could now either calculate the d-prime *manually* (by calculating the rates of hits, false alarms, etc.; z-scoring them and then using the formula above) **OR** you could use a function like **psycho::dprime** to magically calculate d-prime. Note that it may not be as simple as pasting the output of psycho::dprime into a new column. You may need to include an intermediate step.
7. Once you have calculated the dprimes for each participant, compute descriptive statistics for each group. Here, you might find it useful to use something like tapply() , stats::aggregate(), or psych::describeBy(). What is your dependent variable?
8. Decide on an appropriate data visualization for such an experimental design and produce it. You will likely find **{ggplot2}** to be the most useful package for this. There are many suitable options to visualize these data: you can use boxplots, swarm/violin plots, bar graphs, etc. **You should have successfully produced at least one figure before moving to the next step.**
9. The next step is to test for our assumptions. However, in R - the easiest way to do so is to first generate the **anova object** and then use this to test your assumptions. Consult the lecture material and your script from last week if you are unsure of the proper syntax.
10. After testing the assumptions, you can now inspect your anova object. **Which of your effects were significant?**
11. Now is an appropriate time to conduct any planned (or post-hoc) contrasts. Consult the lecture material to find out how to use the **{lsmeans}** package to construct your contrast objects and conduct your tests.

***Effect Sizes***

1. The effect size commonly reported for factorial ANOVAs is ηp2 (partial eta-squared), although η2 (eta-squared) is arguably a more interpretable measure of effect size as it is simply a measure of the variance explained by a factor or an interaction (i.e., the same as *r*2). Unfortunately, the **{lsr}** package discussed previously does not accept ANOVA objects created using many of the functions discussed in the lectures. However, **effectsize::eta\_squared()** will accept an afex ANOVA object and provide you with ηp2.

That being said, **{afex}**calculates effect sizes but does not report them when you run **summary()** on your **{afex}** ANOVA object. To access these, you can use **my\_afex\_ANOVA$anova\_table**, which will give you the F-ratios etc, as well as the generalized eta-squared values (ηG2), which controls for the variance from the other factors.



**Tip: inserting the dollar symbol after an object name will reveal to you what objects, lists, tables, etc, are saved into that object by whichever function you have just used, often helping you narrow down where to find the precise information you are looking for. It is worth placing a dollar symbol after an object name just to explore all the objects it contains.**