Two-Way Mixed ANOVA

Analysis of Variance comes in many shapes and sizes. It allows to you test whether participants perform differently in different experimental conditions. This tutorial will focus on Two-Way Mixed ANOVA.

The term 'Two-Way' gives you an indication of how many Independent Variables you have in your experimental design... in this case: two.

The term 'Mixed' tells you the nature of these variables.

While a 'repeated-measures ANOVA' contains only **within participants** variables (where participants take part in *all* conditions) and an 'independent ANOVA' uses only **between participants** variables (where participants only take part in one condition), **'Mixed ANOVA'** contains **BOTH** variable types. In this case, one of each.

<u>Worked Example</u>

Previous research has found that we are better at recognising faces of our own race compared to those of other races. This tutorial will illustrate how to run a Two-Way Mixed ANOVA using this 'Own-Race Bias' in face recognition.

Imagine that you wanted to investigate whether this own-race recognition advantage exists for Asian and Caucasian adults. You could show participants of both races images of faces that are both Asian and Caucasian. After a short break, you could then show them a larger pool of faces and ask participants to identify whether or not they had seen them before.

In this example, there are **two** independent variables:

- *Race of Participant* which has two levels: *Asian* and *Caucasian*.
- *Face Race* also with two levels: *Asian* and *Caucasian*.

The number of faces participants correctly recognise could be taken as the **dependent variable**.

This is what the data collected should look like in SPSS (and can be found in the SPSS file 'Week 3 ORB Data.sav'):

As a general rule in SPSS, **each row** in the spreadsheet should contain *all* of the data provided by **one participant**.

For **within participants variables**, separate columns need to represent each of the conditions of the experiment (as each participant contributes multiple data points).

Between participants variables are coded in a separate column, where the different levels or conditions of the IV refer to separate individuals.

The different columns in SPSS display the following data:

- **ID_No:** This just refers to the ID number assigned to the participants. We use numbers as identifiers instead of participant names, as this allows us to collect data while keeping the participants anonymous.

- **Race:** This just refers to our *between participants* variable: participant race. As participants were either one race or the other, codes have been used to tell SPSS which condition each of the participants belonged to. In this case:

  1 = Caucasian
  2 = Asian

  Revisit the tutorial *Adding Variables* to see how this is done.

- **Asian_Face:** This column represents one level of our *within participants* IV: race of face. As participants saw all facial stimuli, conditions are represented by different columns. This column contains the number of faces participants correctly recognised when the facial stimuli were Asian.

- **Cauc_Face:** This column represents one level of our *within participants* IV: race of face. It contains the number of faces participants correctly recognised when the facial stimuli were Caucasian.

We will now walk you through how to run a Mixed ANOVA in SPSS

To start the analysis, begin by **CLICKING** on the **Analyze** menu, select the **General Linear Model** option, and then the **Repeated Measures...** sub-option.
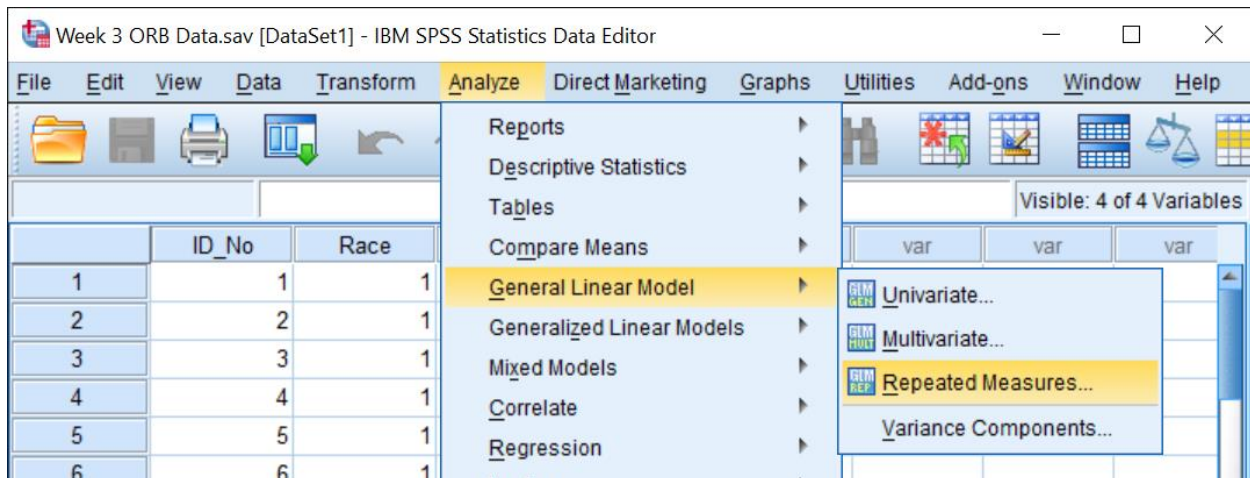

You always select this option, whenever you have a *within participants* variable.

The **"Repeated Measures Define Factor(s)**" box should now appear. This is where we tell SPSS what our within-participants IV is, and how many levels it has.

It doesn't matter what name we give our variable, but it's probably a good idea to give it a sensible name, that we can interpret easily when we look at the output. In this case, let's name our variable *Face_Race* (the underscore is used to separate the words, as SPSS doesn't like spaces in variable names).

We can define our first variable by typing the name (*Face_Race*) into the **Within-Subject Factor Name** box, and entering the number of levels (2) into the **Number of Levels** box:
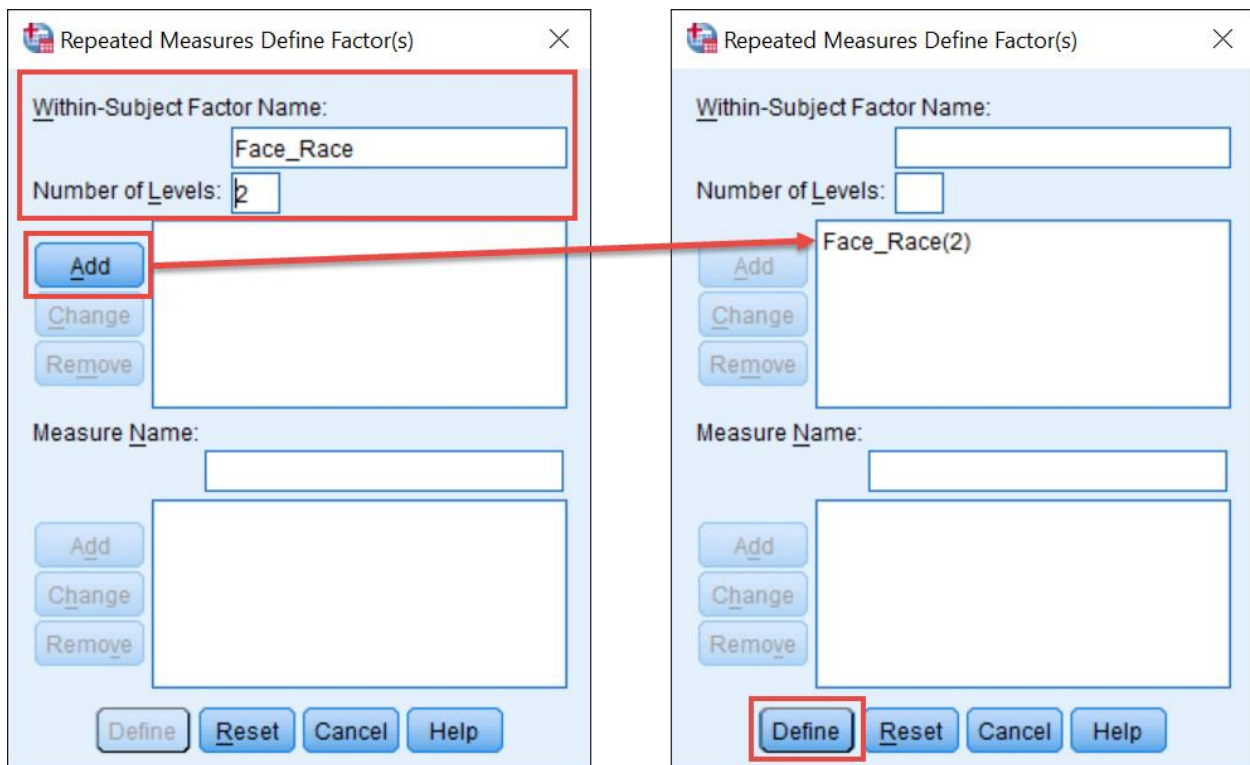

**CLICK** on **Add** to add this variable to the analysis.

Once you have finished defining your IV, **CLICK** on the **Define** button to continue with the analysis

This opens the main ANOVA dialog box.

First, we need to tell SPSS what our between-participants variable is. To do this, **SELECT** the **Participant Race** variable and move it across to the **Between-Subjects Factor(s)** box by **CLICKING** on the blue arrow to the left of the box.
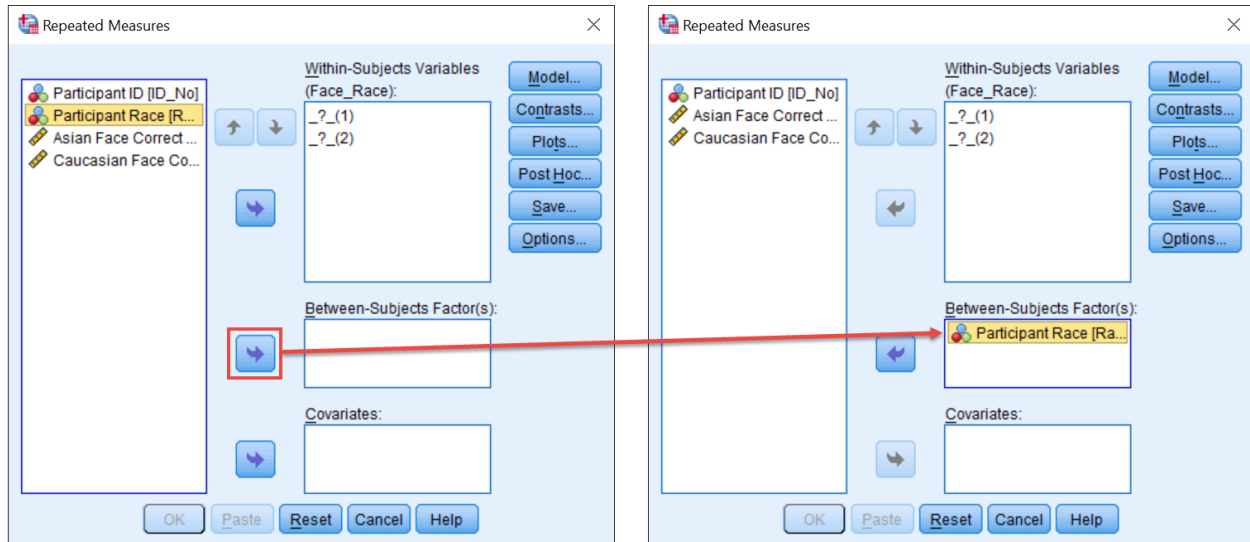
Next, we need to tell SPSS what the conditions of our within-participants variable are. In the **Within-Subjects Variables** box itself, there are a series of question marks with bracketed numbers. These numbers represent the levels of our IVs. Our task is to replace the question marks with the names of the conditions that will map onto the variable level codes.
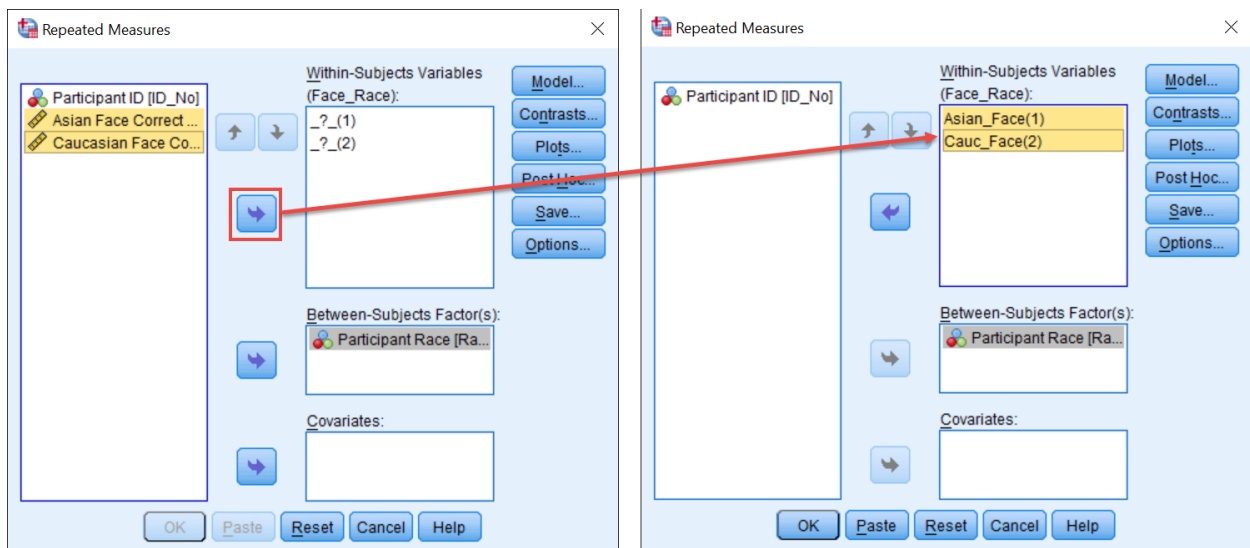
To do this, **SELECT** the two IV conditions: Asian faces and Caucasian faces (when doing this yourself, hold down the **SHIFT** key to select multiple options simultaneously). Now add the conditions to the **Within-Subjects Variables** box by **CLICKING** on the top arrow button.

Now we have told SPSS what is it that we want to analyse, we are almost ready to run the ANOVA. But before we do, we need to ask SPSS to produce some other information for us.
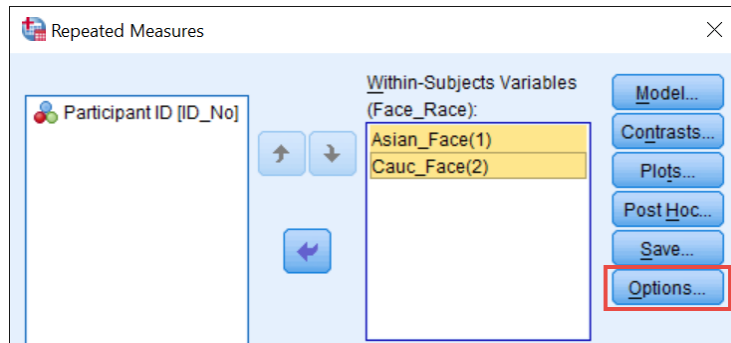
First, we want to ask SPSS to produce some descriptive statistics for our different conditions (i.e. means and standard deviations). **CLICK** on the **Options** button (highlighted in the image above) to do this.

This options the **Repeated Measures: Opens** dialog box. To produce means for the different variables and conditions, highlight all of the factor names in the **Factor(s) and Factor Interactions** box, as is shown here. When doing this yourself, remember that if you hold down the **Shift** key you can click on and highlight all of the factors in one go. (OVERALL) just gives you the overall mean of the whole data set. As we are looking for group differences, this isn't very informative... so it isn't really worth including in this step (although you can if you like)!
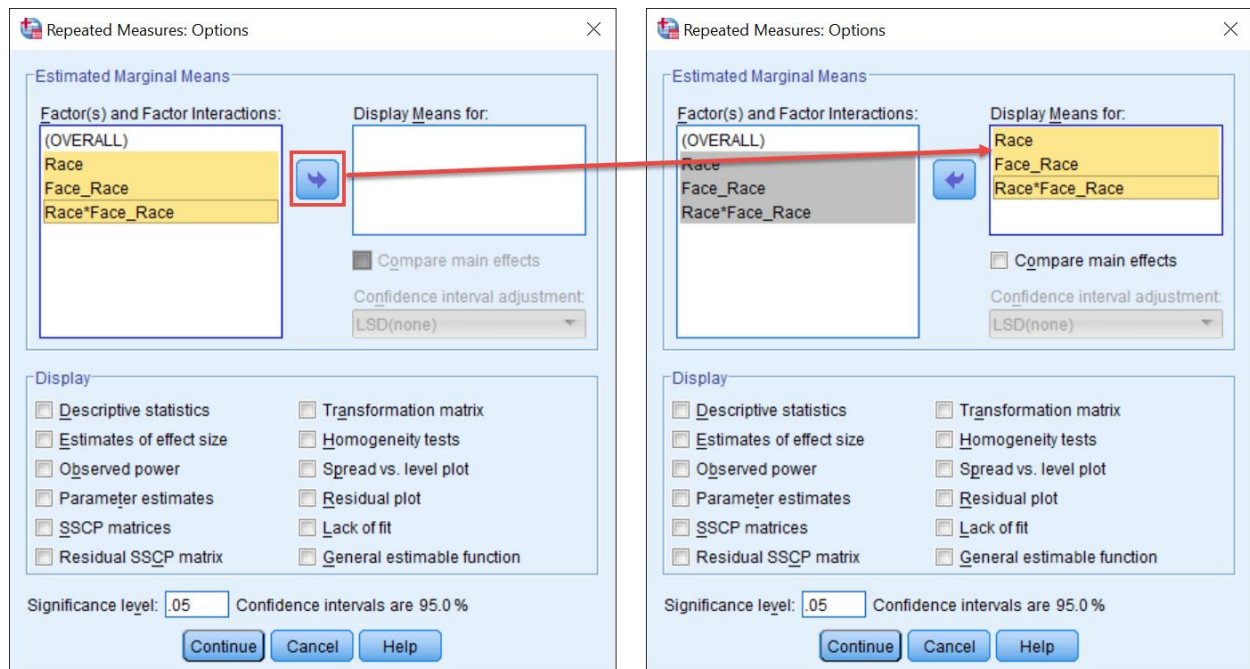
To move the variables across, **CLICK** the arrow (highlighted above).

In the bottom half of the dialog box, there are a number of tick box options that you can select to get more information about the data in your output. In this example we are just going to select three.
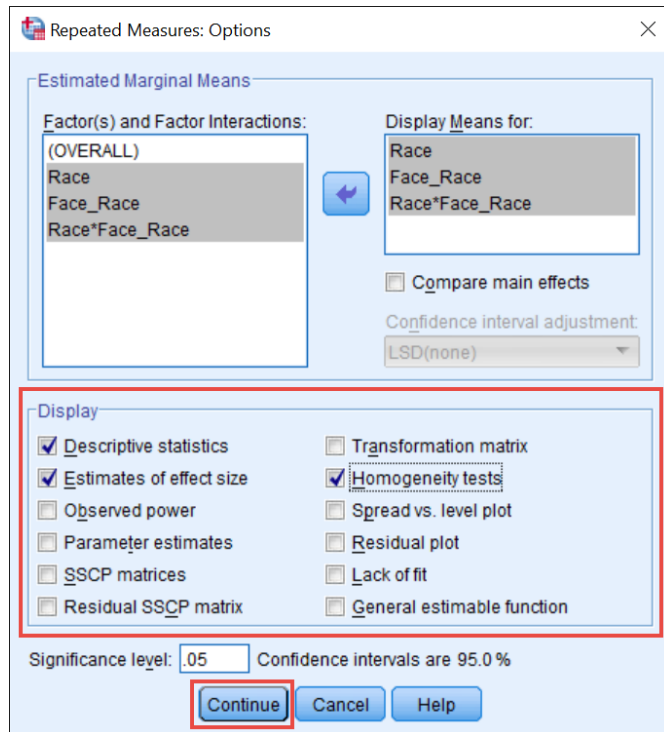
First, **CLICK** on **Descriptive Statistics**, so we can produce our means and standard deviations.

Next, **CLICK** on **Estimates of effect size** to produce effect size information.

Third, whenever you carry out an ANOVA which contains a between-participants variable, the assumption of **homogeneity of variance** must be met. This assumes that the groups you are comparing have a similar dispersion of scores.

To test the assumption, **CLICK** on the **Homogeneity Tests** option now.

Finally, **CLICK** on **Continue** to proceed.

Almost there… but before we can run the analysis, we need to tell SPSS to produce some more things for our output. There are a number of other buttons we could select here. If any of our IVs had more than two levels (or conditions) we would need to select the **Post-Hoc** tests button. But as both *Race of Participant* and *Face Race* only have two, we can skip this option on this occasion. Visit the tutorial on *One-Way Independent ANOVA* to see more about the Post Hoc options available in SPSS.

Instead, we next want to tell SPSS to create a graph of our data for us. This will help us interpret any interaction there might be between the two Independent Variables. **CLICK** on the **Plots** button to do this.
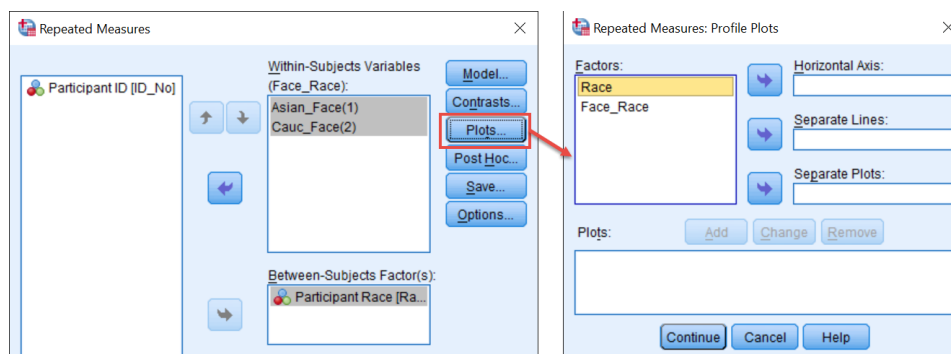
Here we are going to tell SPSS what type of graph we want. While it doesn't really matter which way round you put the variables on the graph, it is usually better to put the IV with the *most* levels on the **horizontal axis** and the other on as **separate lines**.

In this case *both* variables have the same number of levels: two. As such, the order really doesn't matter. As **Race** is already highlighted, start by moving it across to the **Horizontal Axis** box using the top blue arrow. Next, **SELECT** Face_Race and move it across to the **Separate Lines** box using the appropriate arrow.
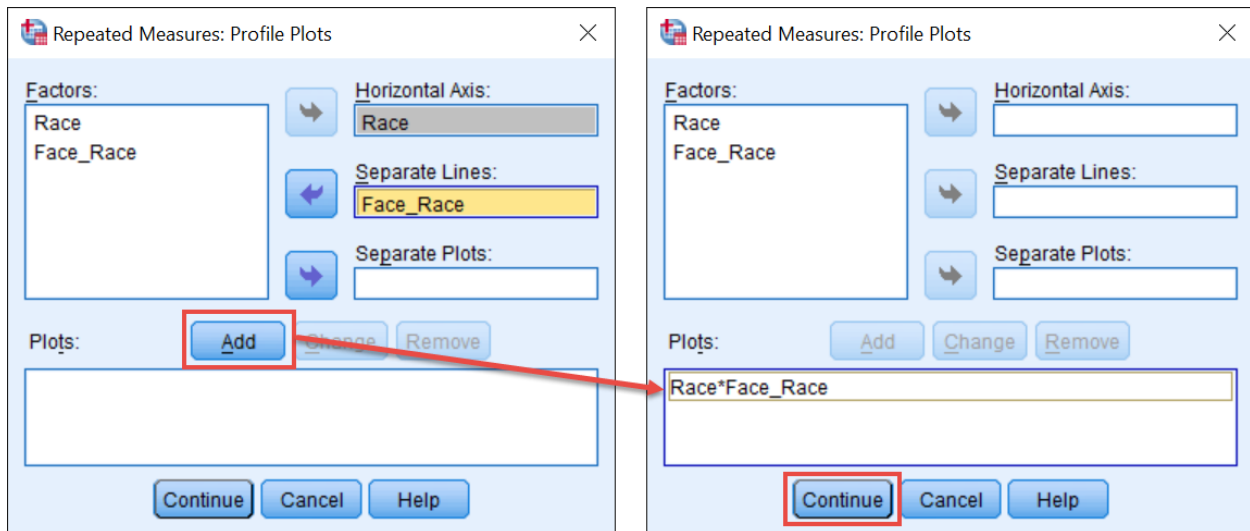
CLICK on the **Add** button to add it to the **Plots** box, and then **CLICK** **Continue** to proceed.
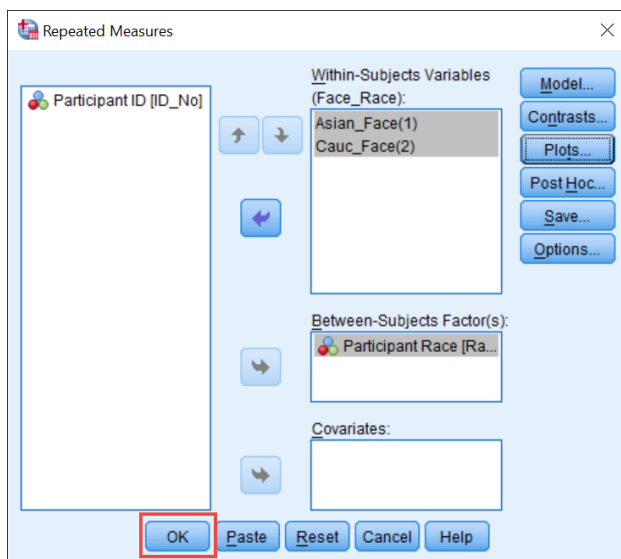
We are now ready to run the analysis!

CLICK **OK** to continue

This opens the **Output** window, where SPSS produces all of the statistics that you asked for:
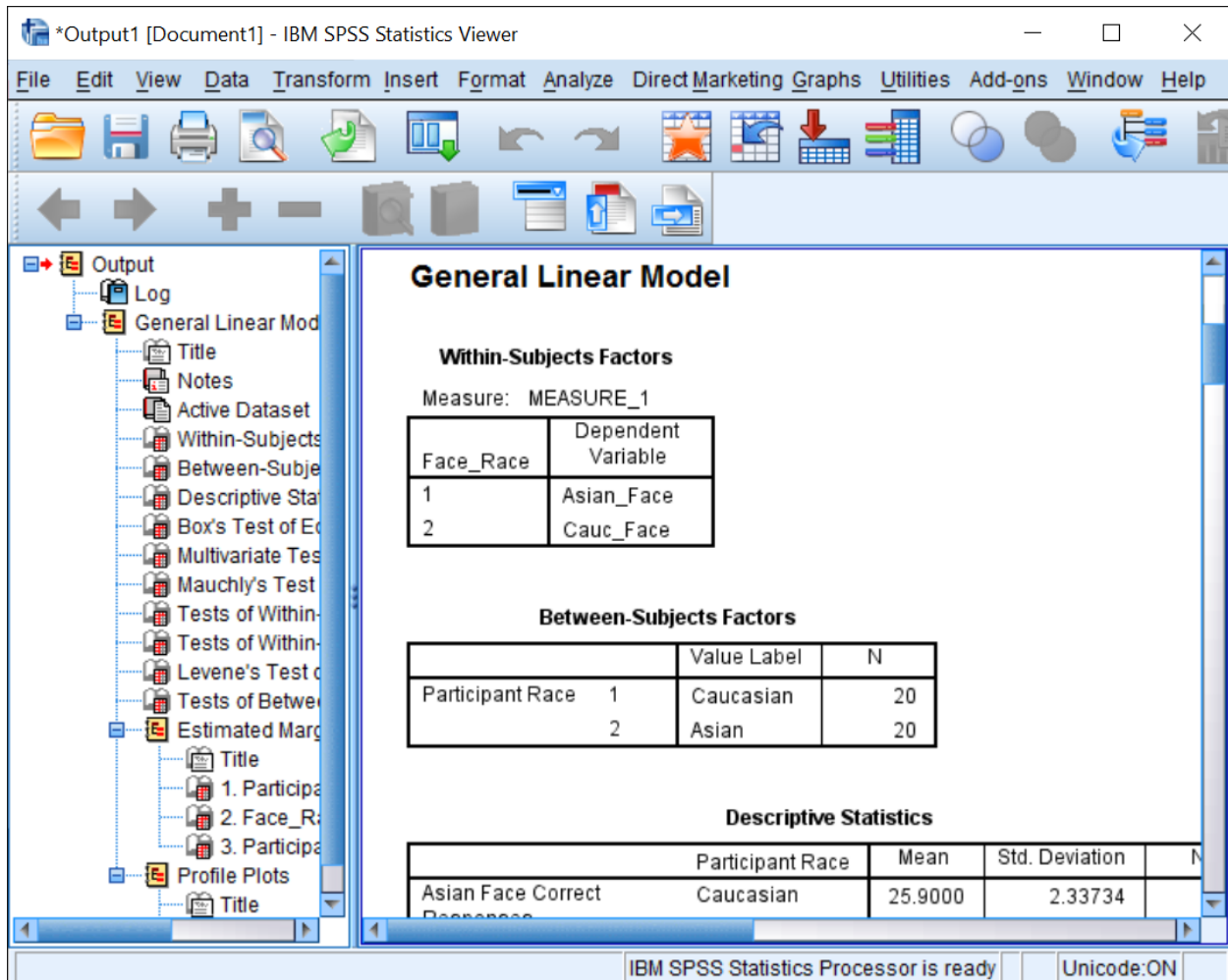
There is quite a lot of output for Analysis of Variance, but don't worry - this tutorial will talk you through the output you need, box by box.

Within-Subjects Factors

This box is just here to remind you what values you have assigned the different levels of your within-participants variable, and what they mean. You may find it useful to refer back to this when interpreting your output.

From looking at the box you should be able to see that for the first factor, **Face_Race**, there are two levels, where: 1=Asian Faces and 2=Caucasian Faces.

Within-Subjects Factors

Measure: MEASURE_1

Face_Race	Dependent Variable
1	Asian_Face
2	Cauc_Face

Between-Subjects Factors

This box is just here to remind you what values you have assigned the different levels of your between-participants variable, and what they mean. You may find it useful to refer back to this when interpreting your output.

Between-Subjects Factors

		Value Label	N
Participant Race	1	Caucasian	20
	2	Asian	20

From looking at the box you should be able to see that for the second factor, **Race**, there are also two levels, where: 1 = Caucasian participants and 2 = Asian participants.

Descriptive Statistics

Descriptive Statistics

	Participant Race	Mean	Std. Deviation	N
Asian Face Correct Responses	Caucasian	25.9000	2.33734	20
	Asian	27.6000	2.30332	20
	Total	26.7500	2.44687	40
Caucasian Face Correct Responses	Caucasian	27.4500	2.21181	20
	Asian	25.9500	2.68475	20
	Total	26.7000	2.54397	40

This table gives you your descriptive statistics. It's good to look at and report these, as they can give you an important insight into the pattern of your data. From this table we can see the average (mean) number of faces recognised for each of the possible variable conditions. You can also see the variation in the data (i.e. spread of scores) for the different groups from the standard deviation.

From this table we can see that on average, the overall Caucasian and Asian participants recognised similar numbers of faces (**means = 26.70 and 26.75 respectively**).

However, the breakdown of conditions showed that for the Asian facial stimuli, Asian participants got more correct responses (**mean = 27.60, SD = 2.30**) than Caucasian participants (**mean = 25.90, SD = 2.34**); but for the Caucasian faces, Caucasian participants (**mean = 27.45, SD = 2.21**) outperformed the Asian participants (**mean = 25.95, SD = 2.68**).

Box's Test of Equality of Covariance Matrices and Multivariate Tests

You only need the next couple of output boxes when you have multiple dependent variables (which we don't). Skip over these and go straight to the **Mauchly's Test of Sphericity** box.

Mauchly's Test of Sphericity

Mauchly's Test of Sphericity[a]

Measure: MEASURE_1

Within Subjects Effect	Mauchly's W	Approx. Chi-Square	df	Sig.	Epsilon[b] Greenhouse-Geisser	Huynh-Feldt	Lower-bound
Face_Race	1.000	.000	0	.	1.000	1.000	1.000

This table tests whether the assumption of sphericity has been met. This is a bit like the assumption of homogeneity of variance for independent tests; and like Levene's test, we *do not* want Mauchly's test to be significant. However, rather than assuming equal levels of variance in the data for the different conditions, in this case we assume that the relationship between the different **pairs of conditions** is similar.

The good news is, you only need to look at this table when you have a within participants variable with more than two levels (i.e. more than one pair)... which in this case, we don't have - **Face_Race** only has two conditions!!

Tests of Within-Subjects Effects

Tests of Within-Subjects Effects

Measure: MEASURE_1

Source		Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Face_Race	Sphericity Assumed	.050	1	.050	.010	.920	.000
	Greenhouse-Geisser	.050	1.000	.050	.010	.920	.000
	Huynh-Feldt	.050	1.000	.050	.010	.920	.000
	Lower-bound	.050	1.000	.050	.010	.920	.000
Face_Race * Race	Sphericity Assumed	51.200	1	51.200	10.588	.002	.218
	Greenhouse-Geisser	51.200	1.000	51.200	10.588	.002	.218
	Huynh-Feldt	51.200	1.000	51.200	10.588	.002	.218
	Lower-bound	51.200	1.000	51.200	10.588	.002	.218
Error(Face_Race)	Sphericity Assumed	183.750	38	4.836			
	Greenhouse-Geisser	183.750	38.000	4.836			
	Huynh-Feldt	183.750	38.000	4.836			
	Lower-bound	183.750	38.000	4.836			

This is the one of the most important tables in the output. It gives you the ANOVA results for your within-participants variable (**Face_Race**); and any interactions with that variable.

The key columns you need to interpret your analysis are:

- **df** stands for <u>**degrees of freedom.**</u> Degrees of freedom are crucial in calculating statistical significance, so we need to report them. For each main effect and interaction there are **two df** values of interest: the factor (or interaction) df and the error term df. In this example the **dfs** can be found in the **Sphericity Assumed** rows (you would only use the other rows if the sphericity assumption had not been met).

- **F** stands for <u>**F-Ratio**</u>. This column gives you the **F-Ratio** statistics calculated by the ANOVA. It is essentially calculated by dividing the systematic variance (i.e. the variation in your data that can be explained by your experimental manipulation) by the unexpected, unsystematic variance. The larger your **F-Ratio**, the more likely it is that your experimental manipulation (your IV) will have had a significant effect on the DV.

  In this example the you need to report the values in the **Sphericity Assumed** rows.

- **Sig** stands for <u>**Significance Level.**</u> This column gives you the probability that the results could have occurred by chance if the null hypothesis were true. The p-value should be smaller than 0.05 for the F-ratio to be significant. If this is the case (i.e. $p < .05$) we reject the null hypothesis and infer that our experimental manipulation (our IV) has had a significant effect.

  However, if the p-value is larger than 0.05, we have to retain the null hypothesis: that there is no difference between the conditions (or no interaction).

- <u>**Partial Eta Squared.**</u> While the *p*-value can tell you whether your main effects and interaction terms are statistically significant, partial eta squared (η_p^2) tells you about the magnitude of these effects. As such, we refer to this as a measure of **effect size**. To interpret your effects sizes, you can use the following cut-offs:
    - 0.14 or more are large effects
    - 0.06 or more are medium effects
    - 0.01 or more are small effects

So we know which columns we need to look at, but what numbers do we use?

Which row you choose depends on whether your assumption of Sphericity has been met. If your Mauchley's test was **non-significant** (i.e. the assumption had been met), **or** if you have less than 3 levels in your within-participants IV (which we do!), then you read across from the **Sphericity Assumed** row. If Mauchley's *had* been significant, then you would need to use one of the other rows.

SPSS groups your analysis into blocks: one block for each variable and interaction.

First, let's look at **Face_Race**.

Tests of Within-Subjects Effects

Measure: MEASURE_1

Source		Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Face_Race	Sphericity Assumed	.050	1	.050	.010	.920	.000
	Greenhouse-Geisser	.050	1.000	.050	.010	.920	.000
	Huynh-Feldt	.050	1.000	.050	.010	.920	.000
	Lower-bound	.050	1.000	.050	.010	.920	.000
Face_Race * Race	Sphericity Assumed	51.200	1	51.200	10.588	.002	.218
	Greenhouse-Geisser	51.200	1.000	51.200	10.588	.002	.218
	Huynh-Feldt	51.200	1.000	51.200	10.588	.002	.218
	Lower-bound	51.200	1.000	51.200	10.588	.002	.218
Error(Face_Race)	Sphericity Assumed	183.750	38	4.836			
	Greenhouse-Geisser	183.750	38.000	4.836			
	Huynh-Feldt	183.750	38.000	4.836			
	Lower-bound	183.750	38.000	4.836			

Using the Sphericity Assumed row, you need to report your results as:

$$F \text{ (IV df, error df)} = \text{F-Ratio}, p = \text{Sig}, \eta_p^2 = \text{Partial Eta Squared}$$

...along with a sentence, explaining what you have found. In this case you might say:

There was no significant main effect of Face_Race on face recognition scores overall (F(1, 38) = .01, p = .92, η_p^2 < .001).

Next, we can use the same method to look at the interaction term. The results are in the **Face_Race * Race** block. Again, using the Sphericity Assumed row to locate the correct values, you might report your results as something like:

There was a significant interaction between Face_Race and Race in terms of recognition scores (F(1, 38) = 10.59, p = .002, η_p^2 = .22).

Tests of Within-Subjects Contrasts

You really don't need to worry about this table for interpreting your results... so skip over this and go straight to your **Levene's Test of Equality of Error Variances** which assesses the assumption of homogeneity of variance for your *between-participants* variable (Race).

Levene's Test of Equality of Error Variances

Levene's Test of Equality of Error Variances[a]

	F	df1	df2	Sig.
Asian Face Correct Responses	.157	1	38	.695
Caucasian Face Correct Responses	1.019	1	38	.319

When conducting an ANOVA with any between-participants variables, one assumption that must be met is that the groups you are comparing have a similar dispersion of scores (i.e. homogeneity of variance). The Levene's Statistic tells us whether or not this is the case.

For Mixed ANOVA, this assumption is assessed at all levels of your within-participants variable (i.e. for both Asian and Caucasian facial stimuli).

If the test is significant this indicates that there are statistically significant differences in the way in the data are dispersed, suggesting that the assumption has been violated. As such, we are looking for a ***non-significant*** result here. In this example, the *Sig.* column tells us that this *is* what we have found as both p-values are greater than .05.

Tests of Between-Subjects Effects

Tests of Between-Subjects Effects

Measure: MEASURE_1

Transformed Variable: Average

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Intercept	57138.050	1	57138.050	8659.007	.000	.996
Race	.200	1	.200	.030	.863	.001
Error	250.750	38	6.599			

This is another one of the most important tables in the output. This is where we get our ANOVA statistics for the between-participants variable (Race).

As with the Tests of Within-Subjects Effects table, the columns we need to interpret your analysis are highlighted above: ***df***, ***F***, ***Sig*** and ***Partial Eta Squared***

In this case we need to read across the row representing our IV (labelled **Race**) and the Error row.

As with the results for the within-participants variables and interaction, you need to report your results using the following formula:

$$F\ (\textit{IV df, error df}) = \textit{F-Ratio}, \text{p} = \textit{Sig}, \eta_p^2 = \textit{Partial Eta Squared}$$

...along with a sentence, explaining what you have found. For example:

There was no significant main effect of Race on face recognition scores overall
(F(1, 38) = .03, p = .86, η_p^2 = .001).

We now have our ANOVA results for both of our IVs (**Face_Race** and **Race**) and the interaction between these variables. But the question is, what does it all mean?

We know that while neither of our IVs produced a significant main effect, we did find an interaction between our IVs... but we now need to interpret and explain what this actually means in English!! To do that, we need to refer back to our **Descriptive Statistics** to see what is happening in each of our different conditions.

Estimated Marginal Means

These boxes show you the breakdown of the means for the different levels of your IVs, and all of the different condition combinations. For a Mixed ANOVA, the mean values are the same as those displayed the **Descriptive Statistics** box at the beginning of your output. Note that these boxes report the Standard Error rather than the Standard Deviation through.

1. Participant Race

Measure: MEASURE_1

Participant Race	Mean	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
Caucasian	26.675	.406	25.853	27.497
Asian	26.775	.406	25.953	27.597

This first box tells you the overall mean recognition scores for both levels of your first IV: **Participant Race**. Here we can see that both Caucasian (mean = 26.68) and Asian (mean = 26.78) participants performed similarly.

2. Face_Race

Measure: MEASURE_1

Face_Race	Mean	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
1	26.750	.367	26.007	27.493
2	26.700	.389	25.913	27.487

The second box tells you the overall mean recognition scores for the levels of your second IV: **Face_Race**. From the very first box in the SPSS output, we saw that 1=Asian Faces and 2=Caucasian Faces.

As such, we can see that overall participants performed similarly for both Asian (mean = 26.75) and Caucasian (mean = 26.70) faces.

3. Participant Race * Face_Race

Measure: MEASURE_1

| Participant Race	Face_Race	Mean	Std. Error	95% Confidence Interval	
				Lower Bound	Upper Bound
Caucasian	1	25.900	.519	24.850	26.950
	2	27.450	.550	26.337	28.563
Asian	1	27.600	.519	26.550	28.650
	2	25.950	.550	24.837	27.063

The final box gives you the breakdown of facial recognition scores for all of your condition combinations. This can help you to interpret your interaction. Again, remembering that the number codes are 1=Asian Faces and 2=Caucasian Faces, we can interpret the pattern of results accordingly.

Here we can see that while Asian participants recognised more Asian faces (**mean = 27.60**) than Caucasian faces (**mean = 29.95**); Caucasian participants showed the opposite pattern (**Asian faces mean = 25.90; Caucasian faces mean = 27.45**), suggestive of an own-race bias in face recognition.

Profile Plots

The final part of the output is the **Profile Plot**. Graphs can be really useful in helping you to visualise and understand your interaction. When looking at the graph, it may help you to consider the following:

- Are the lines doing the same thing... If not, what are they doing?
- Are some points on the graph closer together than others?

Estimated Marginal Means of MEASURE_1
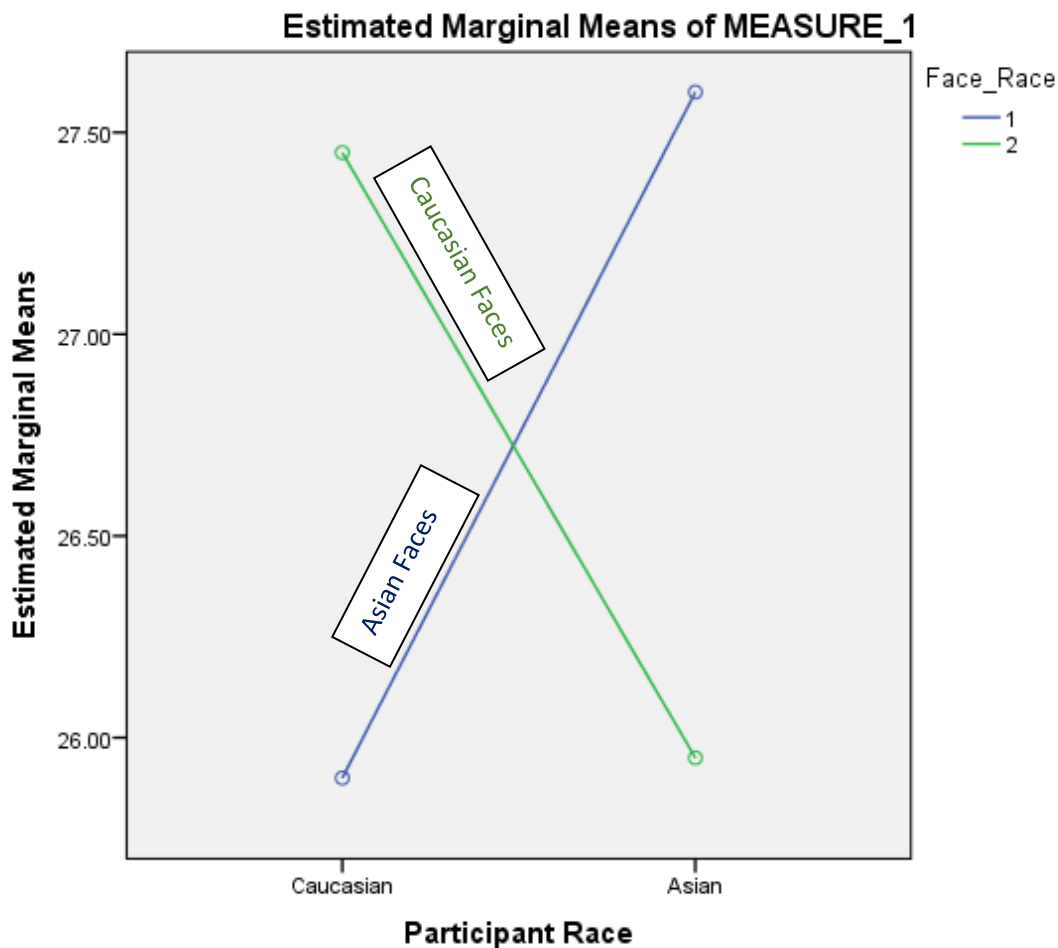
Here, the blue line represents **Face_Race 1** = *Asian Faces*. From the way the line slopes we can see that Asian Participants performed much better for this stimuli than Caucasian Participants.

In contrast, the green line (which represents **Face_Race 2** = *Caucasian Faces*) slopes in the opposite direction. For this stimuli type, Caucasian participants performed better Asian Participants.

As well as looking at the slopes of the lines, we can also look at the vertical distance between the dots for each race of participant. Doing this we can see that both races performed better for faces of their own race, compared to those of the other race. And this own-race advantage was of a similar magnitude in both cases.

The trick now is to put **all** of the information from your output together to make a results section that is sensible and meaningful!!

How do we write up our results?

When writing up the findings from your analysis in APA format, you need to include all of the relevant information covered by the previous slides.

- What were the inferential statistics for your IVs
    - i.e. what were the ANOVA results

- For significant findings, where did the significant difference(s) lie
    - i.e. what were the results of your post hoc tests, if you did them

- What was the pattern and direction of these differences
    - i.e. what were the means and descriptive statistics for your conditions

- If the interaction term was significant, what does it mean in English
    - i.e. describe what was happening in the different conditions

It is usually helpful to the reader of your results if you **include a table of the means and standard deviations** for all of the conditions in your results. It also helps to **include a graph of your results.** You can edit your graph by double clicking on it in the output in SPSS.

For this example, you might end up writing a results section that looks a bit like this:

> **The results of the Two-Way Mixed ANOVA showed that there was no significant main effect of Participant Race ($F(1, 38) = .03$, $p = .86$, $\eta_p^2 = .001$) on face recognition scores, with Caucasian (mean = 26.68) and Asian (mean = 26.78) performing similarly overall.**
>
> **In addition, there was also no significant main effect of Face Race on recognition scores ($F(1, 38) = .01$, $p = .92$, $\eta_p^2 < .001$), with participants showing similar average recognition scores for Asian (mean = 26.75) and Caucasian (mean = 26.70) faces.**
>
> **In contrast, there was a significant interaction between Race of Participant and Face Race ($F(1, 38) = 10.59$, $p = .002$, $\eta_p^2 = .22$). Descriptive statistics showed that while Asian participants performed better for Asian facial stimuli (mean = 27.60, SD = 2.30) compared to Caucasian stimuli (mean = 25.95, SD = 2.68); Caucasian participants showed the opposite pattern (Asian faces mean = 25.90, SD = 2.34; Caucasian faces mean = 27.45, SD = 2.21). From looking at the graph we can see that both races showed a similarly sized recognition advantage for own-race faces.**
>
> **These findings support the notion of an own-race bias in face recognition.**

This brings us to the end of this tutorial. Why not download the data file used in this tutorial and see if you can run the analysis yourself?