Part III - How To in JASP

The examples in this How To have been made in JASP version 0.9.2.0 (JASP Team, 2016), but if you are working with an earlier or later version, the options should be similar. The JASP website itself also has several explanations on how to use the program. These might also be useful to check out:

- https://jasp-stats.org/getting-started/
- https://jasp-stats.org/how-to-use-jasp/

Before you carry out any inferential statistics, it is important that you visually inspect your data by making some plots. You can then calculate some descriptive statistics. JASP has a few options to give you these descriptive statistics.

1.   How To: Descriptive Statistics

1.1   Open data file in JASP

Older versions of JASP can only open .csv files, but if you are working with version 0.8.0.0 or later, you should be able to open .ods files (OpenDocument Spreadsheet), .txt files or .sav files (SPSS data files) as well. If you have an Excel file (extension .xlsx), it is probably easiest to convert it to a .csv file. Please see Practical 1B for details on how to save an Excel file as a .csv file. After you have opened JASP, go to *File > Open* and open your .csv (or .ods, .txt, or .sav) file.

After opening the data, you should always inspect the file and, if necessary, change the measurement scales and add the appropriate labels (also see Practical 1A, assignment 3).

As explained in Practical 1A (assignment 4), you need to save your data as .jasp to keep all the changes to the data, the analyses, and any notes that were added in one file.

1.2   Descriptives

Before you carry out any inferential statistics, it is important that you calculate some descriptive statistics. In JASP, it is very straightforward to calculate the mean, median, range (this gives you the minimum and the maximum), minimum, maximum and standard deviation. Go to *Descriptives > Descriptive Statistics*, and move the dependent variable into the *Variables* box on the right. As explained in Practical 2A (assignment -5) you can split the results by your independent variable, which in the example in Figure III.J.1 is *Group.*
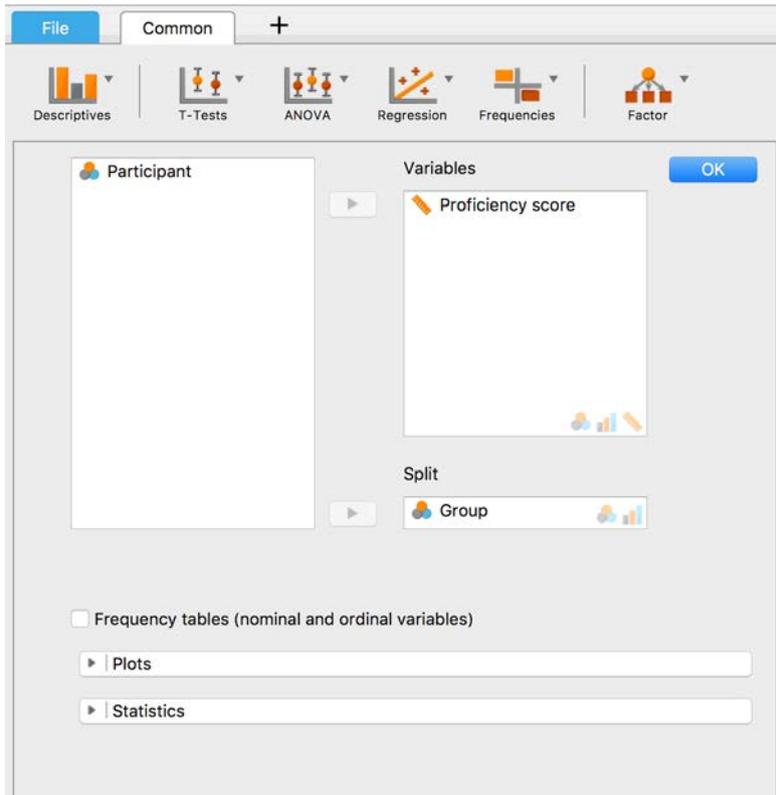
Figure III.J.1 Descriptives menu in JASP

If you click on the *Statistics* option in the bottom of the menu, you will get a menu with the most common descriptive statistics (central tendency, dispersion, and distribution), as can be seen in Figure III.J.2. Select the descriptives that you need.
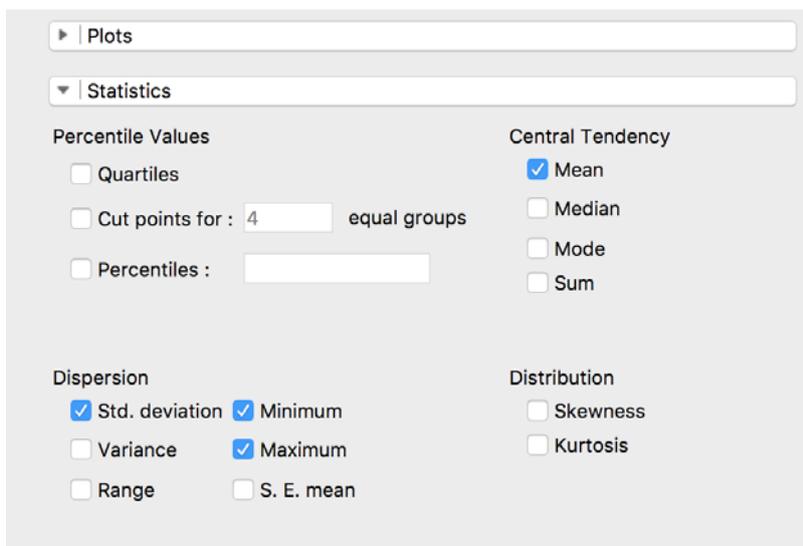

Figure III.J.2. Statistics option in the Descriptives menu

1

1.3. Plots

In addition to calculating descriptive statistics, it is also important to visually inspect your data by making plots. When you are dealing with interval variables only and you mainly want to examine potential relationships between variables, a scatterplot is the best option. A simple scatterplot can be created by going to Plots and in the menu that is shown in Figure III.J.3 select *Correlation plot*.

When you have an independent nominal variable, like *Group*, and you have selected this in the *Split* option above, you will get separate plots for each group. When nothing is moved to the Split field, the analysis for all participants will be shown.
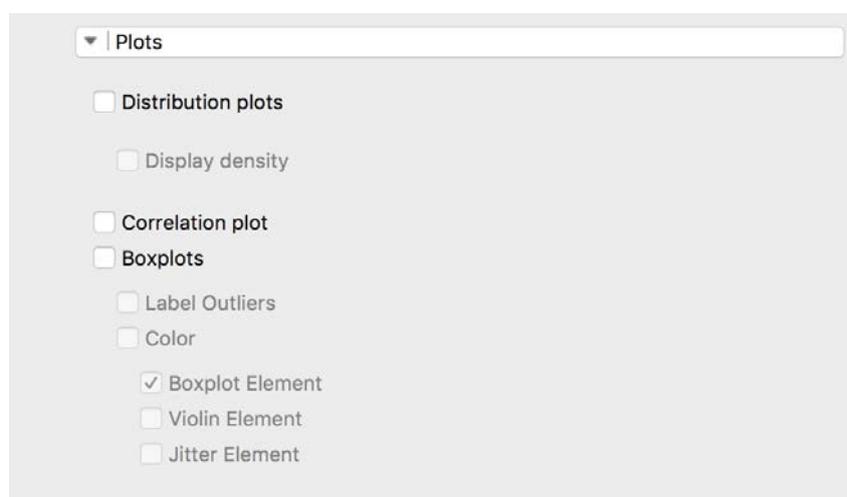
Figure III.J.3. Plots option in the Descriptives menu.

A good way to visualize data, especially when comparing groups, is the Boxplot. For this, you can check the *Boxplots* option. Again, when you have included an independent nominal variable, you will get a boxplot for each group separately. This gives you the opportunity to compare the distribution of the groups, side by side, as in Figure III.J.4.
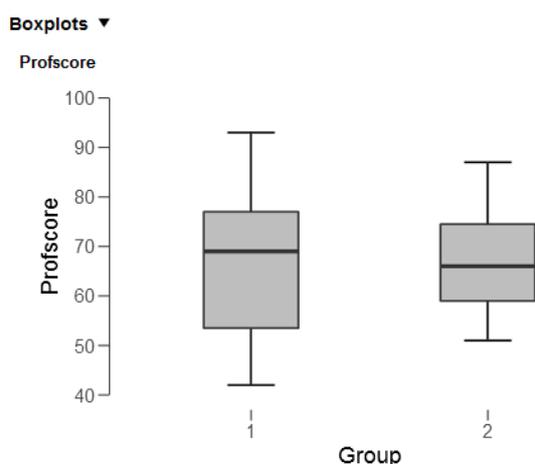
Boxplots ▼

Profscore

Figure III.J.4. Boxplot showing the dispersion in proficiency scores in group 1 (left) and group 2 (right)

1.4   Calculating z-scores

Sometimes you would want to report on z-scores, for example in case you want to know how many standard deviations each participant is away from the mean. JASP allows you to create a formula that adds a column to your data set with the z-score for every participant. You can add this new variable by clicking on the plus-symbol that can be found next to the last column of your data set (see also Practical 3A, assignment 4, for an example). Drag and drop the following to the formula window:

- the dependent variable (DV)
- -
- mean
- DV
- /
- σy
- DV

It should now read: ((DV - mean(DV)) / σy DV.

To complete your action, click on *Compute column*. You now have a column with z-scores for every participant.

In addition to the descriptives mentioned here, it is important to check the assumptions to find out whether you are allowed to conduct the (parametric) test you were aiming for. Checking assumptions will be the main topic of the next How To.

Essential Statistics for Applied Linguistics

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2.   How To: Check Assumptions

Before you carry out inferential statistics, you need to look at the descriptive statistics and check the relevant assumptions for the different parametric tests. This How To will only deal with the practical aspect of how to check some of the assumptions in JASP. For a list and details about all of the assumptions, see Section 4.6 in Part I of the book.

2.1   Checking for normality with interval data

Imagine you are interested in two groups of language learners, a beginner group and an advanced group. They have proficiency scores on a scale from 1 to 100 obtained by means of a multiple choice test. For this design, which can be analysed using an Independent Samples *t*-test, we would have to check normality for each group separately.

A good place to start is by looking at histograms of the data (per group!) and to check whether their shapes approximately follow the bell-shaped curve of the normal distribution. To do this go to *Descriptives > Descriptive Statistics*, and you get the same menu as the one in Figure III.J.1 in the How To Descriptive Statistics Chapter. In the *Variables* box you put your dependent variable, in this case the proficiency score. In the *Split* box, you put the independent variable, Group in this case. You can also look at all of your data together, without selecting an independent variable, but usually, you are interested in the distribution of each individual group.

      The distribution plots under *Plots* will give a first impression of the distribution of the data. These kind of plots are also called histograms. You can select *Display density* or decide to leave it unchecked. See Practical 3C (assignment 3) for more information on how to interpret this difference.

Next, we're going to look at the values of Skewness and Kurtosis, and how much they deviate from zero. Under *Statistics*, you can check the Skewness and Kurtosis boxes. This will give you both values and the standard errors belonging to these values. With these you can calculate the z-scores of skewness and kurtosis by hand, by dividing the skewness and kurtosis values by their standard errors (See Practical 3A for more information).

      Finally, you could perform a Shapiro-Wilk for each group and make sure that these are non-significant to ascertain that your data are normally distributed. For this test of normality in a case of two groups (one nominal independent variable with two levels), you can go to *T-tests > Independent Samples T-test*, add the dependent variable in the *Dependent Variables* box, and the Independent variable in the *Grouping Variable* box. Uncheck the default Test *Student*, and check the option *Normality* under *Assumption Checks* (Figure III.J.5).
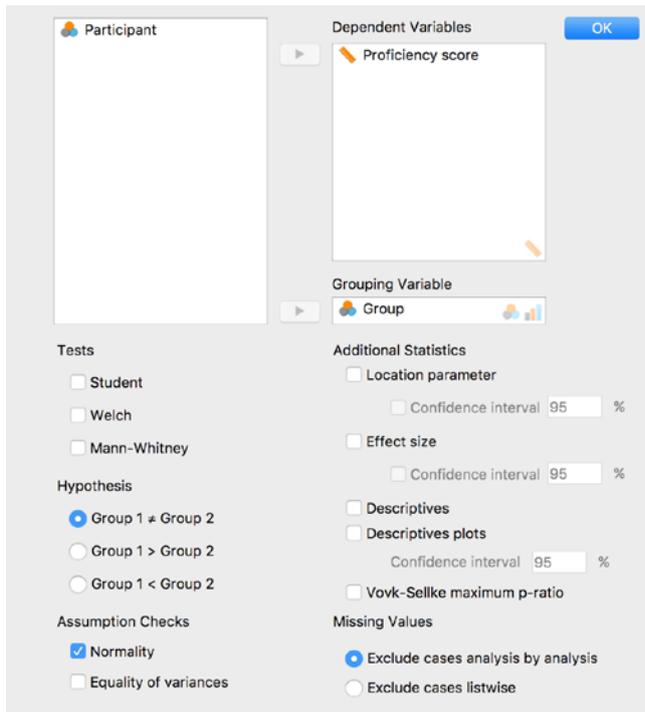
Figure III.J.5. Screenshot of the menu of the Independent Samples t-test

In the output that you generated under Independent Samples t-test you should look for the table as shown in Table III.J.1. You will get a significance value for the Shapiro-Wilk. For both groups, the significance values are $ps > 0.54$. The chance of incorrectly rejecting the null-hypothesis is thus rather large in both cases. Therefore, we do not have to reject the null-hypothesis and can conclude that the data of both the groups are approximately normally distributed.

Table III.J.1 Tests of normality

Test of Normality (Shapiro–Wilk)

		W	p
Proficiency score	Beginners	0.951	0.547
	Advanced	0.973	0.906

Note. Significant results suggest a deviation from normality.

It is always important to use various ways to check your data for normality. Table II.J.2 in Practical 3 of the book provides a rough guideline on how to check for normality with different sample sizes. The Shapiro-Wilk in the example above is the procedure for the Independent Samples *t*-test. Note that for the Paired Samples *t*-test, i.e. when you are testing one group where each participant has two scores, the Shapiro-Wilk is done on the difference between the two dependent variables. Also, in JASP, the Shapiro-Wilk can only be done for *t*-tests. For correlations, the option to check assumptions is not given. In that case

you are limited to checking histograms and the z-scores of skewness and kurtosis. One way around it is to check normality of the variables you want to correlate under One Sample *t*-test. For linear regression and for the ANOVA in JASP, the assumption of normality applies to the residuals (see Section 6.2 in Part I for details). This will be explained in the How To ANOVA and the How To Regression chapters.

In case of violations of normality, you should opt for a non-parametric alternative. See Sections 5.2.1, 5.3.2 (especially Table I.5.9), and 7.4 (especially Table I.7.9) in Part I for an overview of tests that should be used in case one or more assumption of are violated.

2.2   Homogeneity of variance / Homoscedasticity

For mean comparisons, homogeneity of variance is an important assumptions. For correlations and regression analysis, a similar assumption is referred to as homoscedasticity.

2.2.1. Homogeneity of Variance

For the dataset with beginner and advanced learners, we want the variation to be similar in both groups and we can use Levene's test to assess equality of variance (see Sections 4.6 and 5.3.2 in Part I for more details on this assumption). For the Independent-Samples T-test, you can find this under *Assumption Checks*, where you can tick the box for *Equality of variances* (see also Figure III.J.5). In the output window, you look for the table that is similar to the one in Table III.J.2.

Table III.J.2. Outcome of the Levene's test

Test of Equality of Variances (Levene's)

	F	df	p
Proficiency score	2.045	1	0.164

The output for our example shows that the chance of incorrectly rejecting the null-hypothesis is relatively large (16%). Therefore, we can assume equal variances in this case. If the test had been significant, we would have to use a Welch's adjustment to the independent samples *t*-test. (see Section 5.3.2 and 7.4 in Part I, and Practical 3A (assignment 6c) in Part II for details).

2.2.2 Homoscedasticity

Homoscedasticity can best be assessed by creating a scatterplot and, if preferred, adding a regression line to the plot (see Section 6.4 in Part I for details on the concept of homoscedasticity and on how to assess homoscedasticity from a scatterplot). For the following example, imagine a researcher wants to examine the relationship between age of acquisition and proficiency score. To make a scatterplot with two interval variables, we go to *Regression > Correlation Matrix*, add the two interval variables to the right, unselect the box that says *Pearson*, and tick the box that says *Correlation matrix* under *Plots*, as in Figure III.J.6.
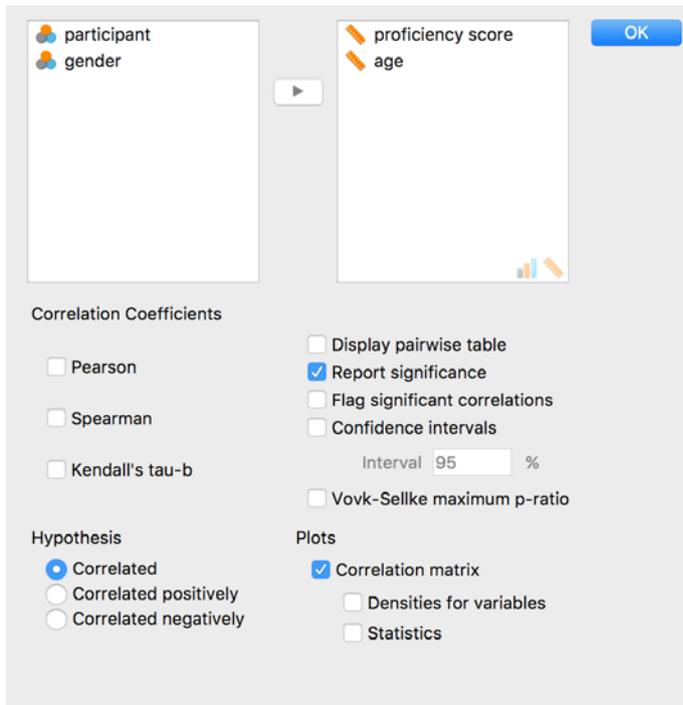
Figure III.J.6. Screenshot of the correlation menu

If you don't see the labels of the x-axis or y-axis well, you can stretch the plot in the bottom right corner of the plot in JASP. Previous versions of JASP would just show the scatterplot, but in the 0.9.2.0 version, the plot will look like the plot in Figure III.J.7. If you want to copy only the scatterplot in for example a research report, you will need to crop the Figure yourself. This might be changed again in future versions of JASP.
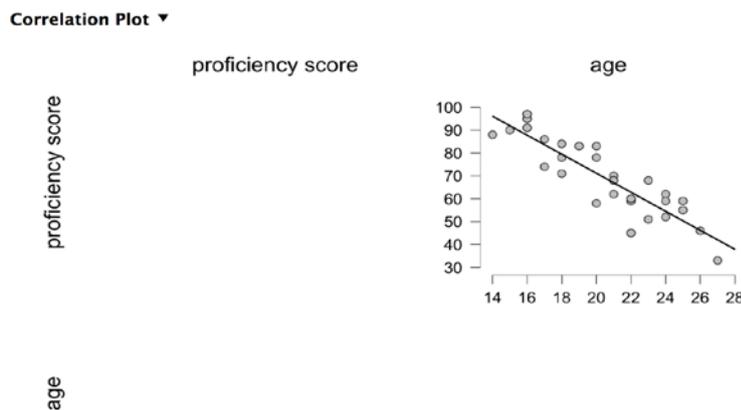

Figure III.J.7 Scatterplot visualizing the relationship between age (x-axis) and proficiency score (y-axis)

Figure III.J.7 suggests no problems with respect to homoscedasticity. Note that, for linear regression, the assumption of homoscedasticity applies to the residuals of your model (also see 'How To Do a Regression Analysis). For correlations, in case of violations of homoscedasticity, it is often better to opt for a Spearman Rho (ρ) or Kendall's Tau (τ) instead of a Pearson (see Section 5.2.1 in Part I for an explanation of when to use which one.

2.3   Linearity and multicollinearity

For correlations and linear regression, linearity is another crucial assumption. Figure III.J.7 clearly reveals a linear relationship between age and proficiency score. See section 4.6 and 6.4 in Part I of the book for more information about linearity and multicollinearity.

In the case of a relationship that is monotonic, but not linear, it would be better to perform a Spearman or Kendall instead of a Pearson correlation (see Section 4.6 and 5.2.1 in Part I).

3. How To: Correlation Analysis

Please note that there are some important assumptions and prerequisites for both the parametric Pearson's *r* (parametric) as well as for the non-parametric Spearman Rho (ρ) and Kendall's Tau (τ) tests. These assumptions are explained in detail in Section 4.6 and 5.2.1 of Part I and a summary of which assumptions to check for correlation can be found in Table I.8.2.

3.1.   Correlations: Checking assumptions and plotting the data

For this example, we want to find out whether there is a relationship between two interval variables, age of acquisition and French proficiency scores, so we will aim for a Pearson *r* correlation (also see Section 5.2.1).

In JASP, open your .csv file. To check for normality with this particular sample, we can follow the instructions in the 'How to Check Assumptions') for Skewness and Kurtosis and histograms. You can also go to *T-tests > One Sample T-test*, move both variables you want to check to the right, checking the box for *Normality* under *Assumption Checks*, and deselecting *Student* under *Tests*, as can also be seen in Figure III.J.8. Remember that Table II.J.2 in Practical 3 of the book provides a rough guideline on how to check for normality with different sample sizes.
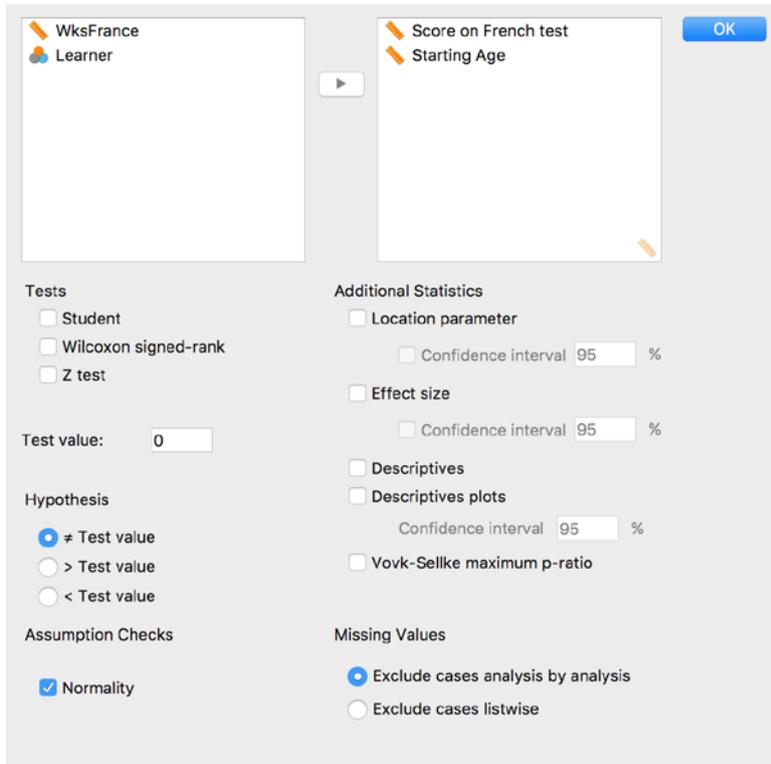
Figure III.J.8. Screenshot of One Sample T-test used to check normality

Table III.J.3 shows that the data are normally distributed, so we can proceed to carry out a Pearson *r* correlation. When the data are not normally distributed, you should opt for a non-parametric alternative instead (see Section 5.2.1 in Part I for details).

Table III.J.3 Screenshot of the output of the Normality test

Test of Normality (Shapiro–Wilk) ▼

	W	p
Score on French test	0.977	0.885
Starting Age	0.960	0.551

Note. Significant results suggest a deviation from normality.

Next, we want to get to know the data further and this is best done by plotting them in a scatter plot. We do this by going to *Regression > Correlation Matrix* and ticking the box for *Correlation Matrix* under *Plots*. We want to make sure that the "independent" variable (in this case Starting Age is more of an independent variable) is on the x-axis, so we first add the "dependent" variable to the box on the right, followed by the "independent" variable. Figure III.J.9 shows us that the relationship is linear and homoscedastic (see Section 4.6 and 6.4 for details on these assumptions).
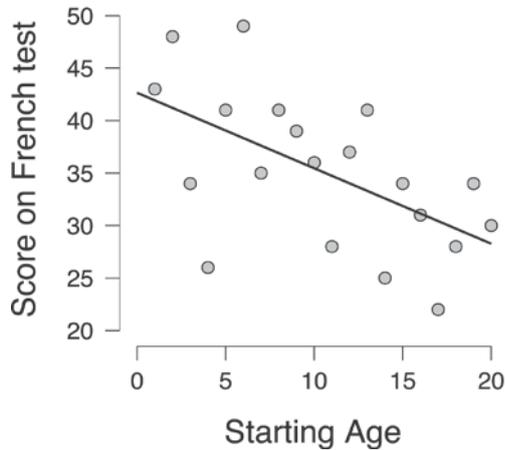
Figure III.J.9 Adapted scatterplot from JASP output (see How to Check Assumptions on why this plot has been adapted)

3.2   Correlations: getting results

To do a correlation analysis, again go to *Regression > Correlation Matrix*. When you are in the menu (see Figure III.J.10), move the variables you want to test to the right. Next, select which statistical test you want to carry out (*Pearson*, *Spearman*, or *Kendall's tau-b*), select Confidence Intervals, and click OK. You can also select *Display pairwise table*, which will yield a table such as the example in Chapter 5 of Part I (see Table I.5.2). Selecting the option *Flag significant correlations* will add asterisks to denote the significance (* for <.05, ** for < .01, and *** for <.001).
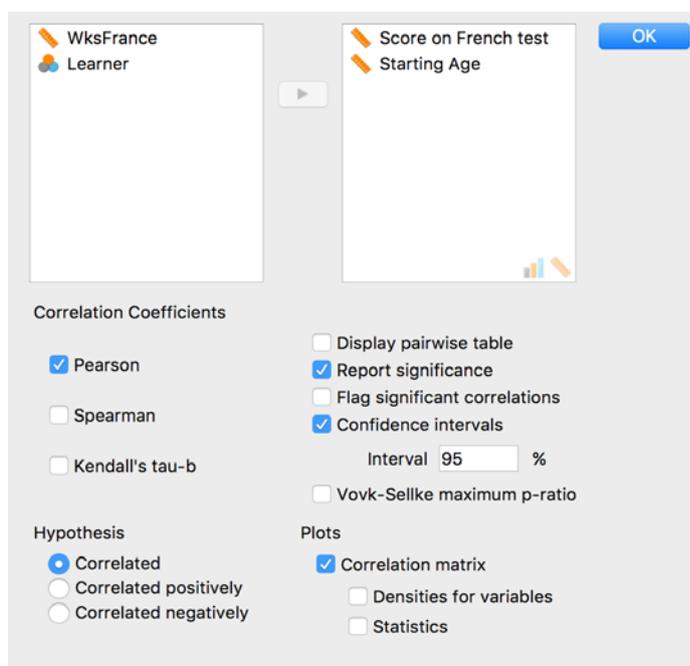

Figure III.J.10. Screenshot of the Correlation Matrix menu in JASP

3.3   Correlations: interpreting the output

In Table III.J.4, we can see that the significance value is p = 0.008, and that our correlation of -0.572 is a moderately strong, negative correlation.

Table III.J.4. Output of the Correlation analysis in JASP.

Pearson Correlations ▼

		Score on French test	Starting Age
Score on French test	Pearson's r	—	
	p–value	—	
	Upper 95% CI	—	
	Lower 95% CI	—	
Starting Age	Pearson's r	−0.572	—
	p–value	0.008	—
	Upper 95% CI	−0.173	—
	Lower 95% CI	−0.810	—

For details on how to interpret this output, please see Section 5.2.1 in Part I and Practical 4A-7 in Part II.

3.4   Correlations: reporting results

You can use the template explained in detail in Practical 4A (assignment 8) and report the results as follows:

A Pearson correlation analysis showed that the age at which one starts learning a foreign language and proficiency were significantly negatively related (r (18) = -0.572, p = 0.008, 95% CI [-0.17, -0.81]). This strong relationship suggests that the later one starts learning a foreign language, the lower their proficiency level will be, as can also be seen in Figure III.J.9.

3.5   Correlations: additional useful information to check

The effect size is quite large in this study, which could potentially mean that this is a meaningful effect in terms of power, but we know that we don't have 28 participants. As explained in Practical 5A (assignment 10), we could run a power test using one of the options mentioned there.

4. How To: Chi-square Analysis

Chi-square is a non-parametric test for frequency analysis and is used to assess whether there is an association between two nominal/categorical variables. Before you can run a Chi-Square test, remember that you should check the three assumptions that have to be met (see Section 5.2.3 and Practical 4B, assignment 5, for details).

4.1   The Chi-square test: entering the data

Suppose we investigated the colour preference of men and women using a questionnaire that only allowed the participants to choose between red, yellow and blue. The contingency table may look something like Table III.J.5.

Table III.J.5. Contingency table with the total counts of the colour preferences of female and male participants.

Colour	Female	Male
Blue	29	42
Red	28	24
Yellow	23	23

Having the data in this format, the data in JASP would be organized as in Figure III.J.11. There is also an option to run a Chi-Square analysis on the raw data. Please see Practical 4B, assignment 4, for an explanation of the two formats.
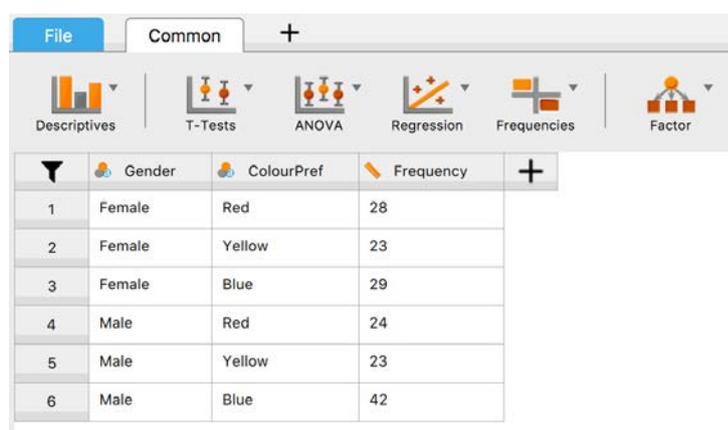
Figure III.J.11. Screenshot of how the data should be organized if you only know the total frequencies for each cell

4.2   The Chi-Square test: choosing the variables in the menu

Once you have the data open in the format of one of both options, go to *Frequencies > Contingency Tables*. For the raw data, you would only put a variable in *Rows*, and a variable

in *Columns*. For the data organized by the total counts, you would add the *Frequency* column in the box for *Counts*. This is also illustrated in Figure III.J.12.
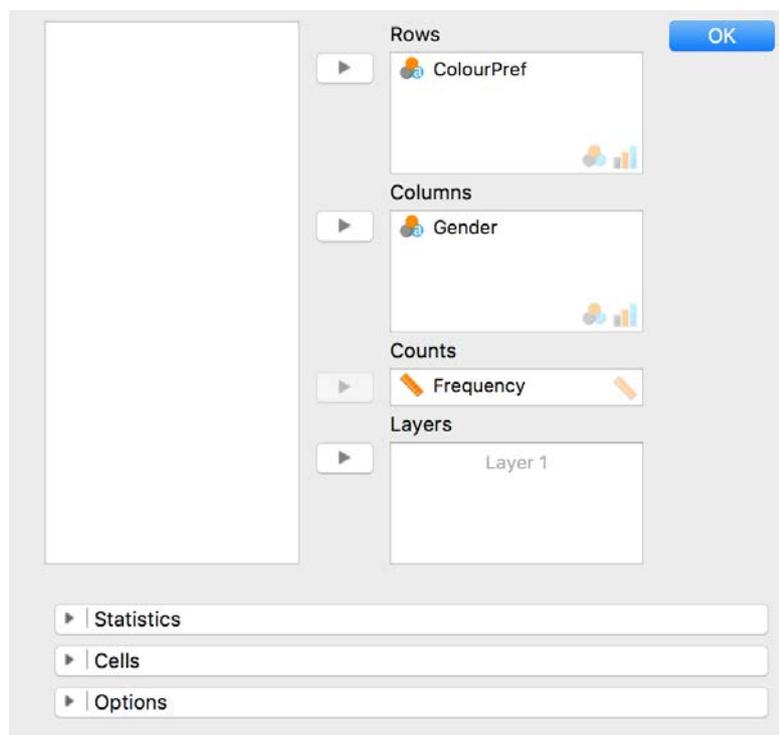
Figure III.J.12. Screenshot of the menu in Option 2

4.3   The chi-square test: checking the assumptions

As explained in Practical 4B (assignment 5), we must check if the assumptions for the chi-square analysis have been met, before we look at the Chi-Square analysis itself. We can do this in the same Menu by clicking on *Cells* and checking the box for *Expected* under *Counts*. Under *Statistics*, you want to deselect the χ^2 (Chi-Square) symbol, since we are not interested in that yet. This is illustrated in Figure III.J.13. Now click OK.

Figure III.J.13. Screenshot of the menu when checking for the expected values

Next, we will look at the output and check whether the conditions have been met (screenshot of the table in Table III.J.6).
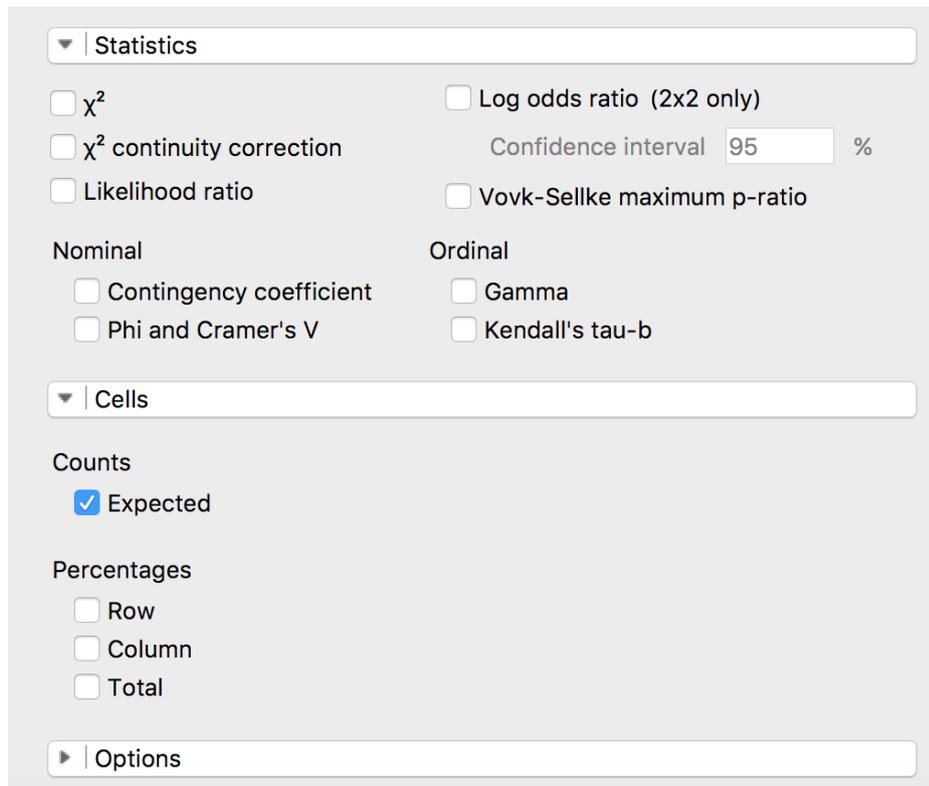
Table III.J.6 Screenshot of the output table with the Expected counts.

Contingency Tables

ColourPref		Female	Male	Total
		Gender		
Blue	Count	29.00	42.00	71.00
	Expected count	33.61	37.39	71.00
Red	Count	28.00	24.00	52.00
	Expected count	24.62	27.38	52.00
Yellow	Count	23.00	23.00	46.00
	Expected count	21.78	24.22	46.00
Total	Count	80.00	89.00	169.00
	Expected count	80.00	89.00	169.00

In our case, all of the Expected values are above 5, so there is no reason to worry and we can continue to the next step, which is looking at the Chi-Square outcome. Please see Practical 4

4.4   The chi-square test: getting results

To run the Chi-Square analysis again go to Frequencies > Contingency Tables. Enter the variables again, as we did in Figure III.J.12. Click on *Statistics*, and tick the box of the statistical test, in this case, you want the χ^2 which is already selected by default. You also want to select Phi and Cramer's V..

Click on Cells and check *Row*, *Column*, and *Total* under *Percentages*. Now click OK.

4.5   The Chi-square test: interpreting the output

The first table in the output (see Table III.J.7) gives us the descriptives we asked for.

Table III.J.7. Screenshot of the Contingency table

Contingency Tables ▼

ColourPref		Female	Male	Total
		Gender		
Blue	Count	29.00	42.00	71.00
	% within row	40.85%	59.15%	100.00%
	% within column	36.25%	47.19%	42.01%
	% of Total	17.16%	24.85%	42.01%
Red	Count	28.00	24.00	52.00
	% within row	53.85%	46.15%	100.00%
	% within column	35.00%	26.97%	30.77%
	% of Total	16.57%	14.20%	30.77%
Yellow	Count	23.00	23.00	46.00
	% within row	50.00%	50.00%	100.00%
	% within column	28.75%	25.84%	27.22%
	% of Total	13.61%	13.61%	27.22%
Total	Count	80.00	89.00	169.00
	% within row	47.34%	52.66%	100.00%
	% within column	100.00%	100.00%	100.00%
	% of Total	47.34%	52.66%	100.00%

In the next table, which can be seen in Table III.J.8, we find that the χ^2-value is 2.215 and the chance of incorrectly rejecting H_0 is 0.33. Note that the degrees of freedom (df in Table III.J.9) in a Chi-Square analysis is not related to the number of participants, but to the number of cells.

Table III.J.8. Screenshot of the output of the Chi-Square test.

Chi-Squared Tests

	Value	df	p
χ^2	2.215	2	0.330
N	169.0		

Clearly, the effect in the current study did not reach significance. If the result had been significant, we would probably want to look at the table with the values for Phi and the Cramer's V we asked for (shown in the third table, also in Table III.J.9). Cramer's V, which can be found in the bottom line of Table III.J.9, confirms that we are dealing with a very small effect (for details on effect sizes for Chi-square and how to interpret them, see Section 5.2.3 and Practical 4B, assignment 7.

Table III.J.9. Screenshot of the table with effect sizes.

Nominal

	Value
Phi–coefficient	NaN[a]
Cramer's V	0.114

[a] Value could not be calculated – At least one row or column contains all zeros

4.6 The Chi-square test: reporting on the results

Conventionally, the results of the Chi-square should be reported as follows:

A Chi-square analysis revealed that the association between gender and colour preference was not significant χ^2 (2, N=169) = 2.22, p = 0.33.

In the case of significant results, do not forget to also explicitly report on the direction of the association (e.g. men having a stronger preference for Blue), and add the effect size (see Practical 4B, assignment 9, for more details on how to report on the results).

When describing your results in a research report, always also include the contingency table (with observed values). The example table in Table III.J.10 has been copied from JASP without the Percentages (clicking again on *Frequencies > Contingency Tables* and unchecking the Percentages). After it was copied into Word, the whole table was selected, the font was changed and by right-clicking and selecting Autofit > Fit to Window, the table was enlarged a bit. You can also remove the decimals since we are dealing with absolute numbers.

Table III.J.10. Contingency table showing the total counts of the Colour preferences of Male and Female participants.

Contingency Tables

ColourPref	Gender		Total
	Female	Male	
Blue	29	42	71
Red	28	24	52
Yellow	23	23	46
Total	80	89	169

Another valuable addition to the report is a barplot. This is not possible in the current version of JASP, but may be added in the future. Until then, the only way to visualize the data is to make histograms. For more information see Practical 4B-8.

Essential Statistics for Applied Linguistics

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5. How To: *t*-test

As with all parametric tests, please bear in mind the important assumptions and prerequisites for the *t*-test before conducting the actual test (also see Sections 4.6 and 5.3). As mentioned in Section 5.2.3, there are several versions of the t-test available, all with their own set of assumptions. As an example, we will be demonstrating the *independent samples t-test* here.

5.1 The Independent Samples *t*-test: preparing for the *t*-test

For the present purposes, we will use a dataset comparing test scores of boys and girls. It is good practice to always start with an inspection of the data by looking at some descriptive statistics for both groups. These descriptive statistics can be calculated in the *Descriptive Statistics* menu under *Descriptives* (see Practical 2A and Practical 3A, assignment 2a, for details). Table III.J.11 shows the results for the data set used here.

Table III.J.11 Descriptive Statistics of the t-test dataset of boys and girls

Descriptive Statistics ▼

	score	
	boys	girls
Valid	20	20
Missing	0	0
Mean	32.10	37.90
Std. Deviation	4.553	3.177
Minimum	25.00	32.00
Maximum	42.00	45.00

The output already shows that the girls seem to score higher on average (M= 37.9;SD=3.18) than the boys (M= 32.1;SD=4.55). A simple boxplot, such as the one in Figure III.J.14 will also give a lot of information about the spread of the scores in both groups, as was also discussed in How To Do Descriptives.
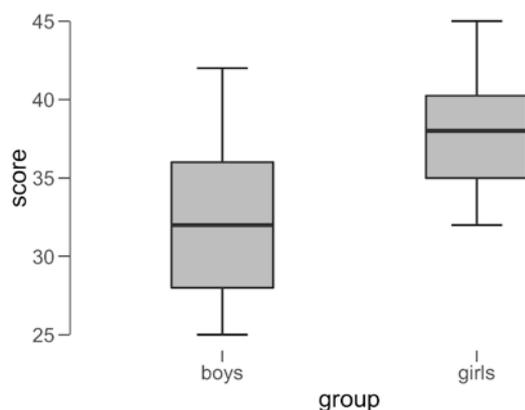

Figure III.J.14 Boxplot of the two groups and their test scores.

5.1.1 Checking normality

To check for normality. we will here look at the z-scores of skewness and kurtosis, and by checking the Shapiro-Wilk test of normality in the menu of the Independent Samples t-test. Please note that this is not always the best option for a normality check: Table II.J.2 in Practical 3 of the book provides a guideline on how to check for normality in different circumstances.

The Shapiro-Wilk tests in Table III.J.12 show that the difference between our sample's distributions and the normal distribution is not significant.

Table III.J.12 Outcomes of Normality test

Test of Normality (Shapiro–Wilk) ▼

		W	p
score	boys	0.965	0.644
	girls	0.976	0.869

Note. Significant results suggest a deviation from normality.

In addition, the z-scores for Skewness and Kurtosis are within the required range. These are calculated by taking the values of skewness and dividing these by their standard error. If we take the skewness value of the boys from Table III.J.13, which is 0.2292, and we divide it by its standard error, 0.5121, we get a value of 0.45, which is well within the range (see Table II.J.2 in the book for details on this interpretation).

Table III.J.13 Values of skewness and kurtosis and their standard errors.

Descriptive Statistics

	score	
	boys	girls
Valid	20	20
Missing	0	0
Skewness	0.2292	0.2873
Std. Error of Skewness	0.5121	0.5121
Kurtosis	−0.4325	−0.09148
Std. Error of Kurtosis	0.9924	0.9924

5.1.2 Checking Homogeneity of Variance

We will check homogeneity of variance (also see Section 4.6 in Part I) using Levene's Test in the menu of the Independent Samples t-test and was also explained in the How to Check Assumptions Chapter.

The significance value for the test of homogeneity of variance in our example is $p = 0.09$ (see Table III.J.14), so we can assume equal variances in this case.

Table III.J.14 Values of skewness and kurtosis and their standard errors.

Test of Equality of Variances (Levene's)

	F	df	p
score	2.969	1	0.093

5.2   The Independent Samples *t*-test: performing the *t*-test

In the JASP menu, select the *Independent Samples T-Test* under *T-Tests*. In the menu that pops up (see Figure III.J.15), move the dependent variable and the independent variable you want to test to the boxes on the right. You want to select *Student* under *Tests*Also select *Location parameter* together with the *Confidence Interval* below it. Finally, under *Additional Statistics*, you want to select the *Effect size*, *Descriptives* and also *Descriptives Plots*.
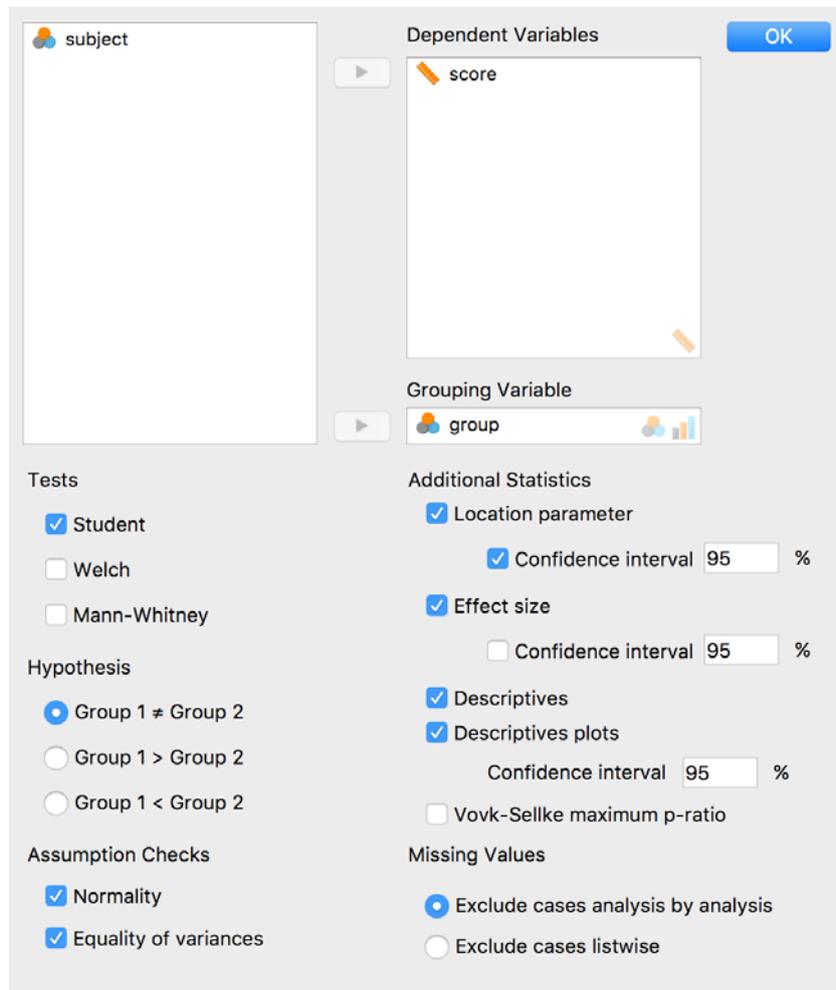

Figure III.J.15. Screenshot of the Independent Samples t-test menu

5.3   The independent-samples t-test: interpreting the output

The output in Table III.J.15 Shows that the girls scored higher than the boys and now also reveals that this difference is significant. For a detailed explanation on how to interpret the output of a t-test, please see Practical 4C, assignment 9.

As explained in detail in Chapter 4 of Part I of the book, we also want to know the size of the effect. The one that is calculated here is Cohen's d, but you can also choose to calculate r^2 (see Practical 4C, assignment 11 and 12, for details on both these effect sizes and how to calculate them)..

The effect size in Table III.J.15 is large (see Table I.5.10 for details on how to interpret these effect sizes) and this information, either with the value of r^2 or the value of d, should be added to the report.

Table III.J.15 Independent samples test outcome

Independent Samples T-Test

						95% CI for Mean Difference		
	t	df	p	Mean Difference	SE Difference	Lower	Upper	Cohen's d
score	−4.672	38.00	< .001	−5.800	1.241	−8.313	−3.287	−1.477

Note. Student's t-test.

5.4   The independent-samples t-test: reporting on results

On average, the girls scored higher (M = 37.9, SE = 0.71) than the boys (M = 32.1, SE = 1.02) on an intelligence test. This difference was significant (t(38) = −4.67; p < .001), 95% CI [-8.3, -3.2] and is also visible in Figure III.J.14 . The effect size was large: d = -1.48.

The plot is referring to the box plot that was shown earlier. Alternatively, you may also copy the plot that is generated by the Independent Samples t-test menu, as the one in Figure III.J.16.
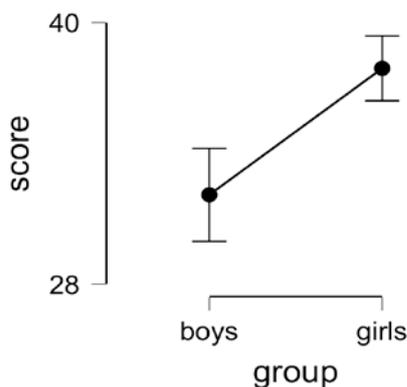

Figure III.J.16 Descriptives plot of the different groups. The error bars indicate the 95% CI

6. How To: Simple Regression Analysis

Regression is a statistical model used for assessing relationships. More specifically, it helps to predict to which extent one or more independent variables contribute to the value of a dependent variable. Regression has its own particular list of assumptions that has been dealt with in detail in section 6.4 of Part I

As the assumptions mostly apply to the residuals of the model, they are generally checked after fitting the model.

6.1 Simple Regression: opening and inspecting the data

Imagine a researcher is interested in the impact of age on the results of a simple lexical decision task. To explore the data and the potential relationship between the variables, it would be helpful to create a scatterplot. We get this by going to Regression > Correlation Matrix. Because we want the Reaction Times on the y-axis, and the Age on the x-axis, we put RT first and then Age. The scatter plot can be seen in Figure III.J.17.
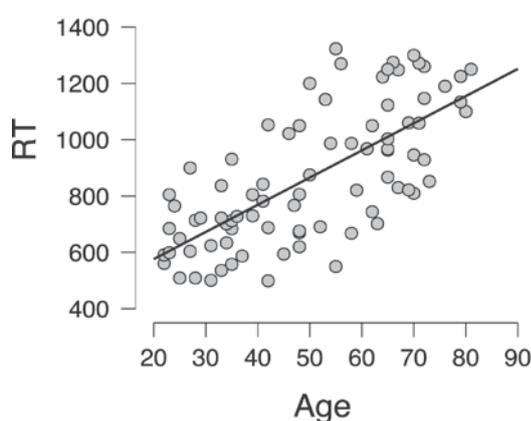

Figure III.J.17 Scatter plot showing the relationship between Age (x-axis) and RT (y-axis)

The pattern in Figure III.J.17 reveals that there seems to be a linear positive relationship between age and RT in the lexical decision task.

6.2 Simple Regression: fitting the model and interpreting the output

A simple regression model can be built by going to *Regression > Linear Regression*, putting RT in the *Dependent Variable* box and Age in the *Covariates* box.

As explained in Chapter 6 of Part I and in Practical 5B, assignment 6, there are different tables in the output giving different information. These can be seen in Table III.J.16. The output reveals that there is a significant effect of age: for every year added to age, the RT slows down with 9.6 ms.

The R-squared reveals that about 50% of the variance can be explained by our model, which is quite good. The second table gives the outcome of an ANOVA.

For more details on how to interpret the output, including all other values, please see Section 6.2 and, in particular, the explanation of Table I.6.4 in Part I of the book.

Table III.J.16 Three output Tables of Simple Regression.

Model Summary

Model	R	R²	Adjusted R²	RMSE
1	0.704	0.496	0.489	170.3

ANOVA

Model		Sum of Squares	df	Mean Square	F	p
1	Regression	2.278e +6	1	2.278e +6	78.57	< .001
	Residual	2.319e +6	80	28991		
	Total	4.597e +6	81			

Coefficients

Model		Unstandardized	Standard Error	Standardized	t	p
1	(Intercept)	383.129	57.686		6.642	< .001
	Age	9.649	1.089	0.704	8.864	< .001

6.3   Simple Regression: checking assumptions

6.3.1 Linearity and Homoscedasticity

The best way to check linearity and homoscedasticity is by creating a residuals plot. This can be found in the *Linear Regression* menu under *Plots*. To get the plot that you want tick the one that says *Residuals vs. predicted*, as can be seen in the screenshot in Figure III.J.18.
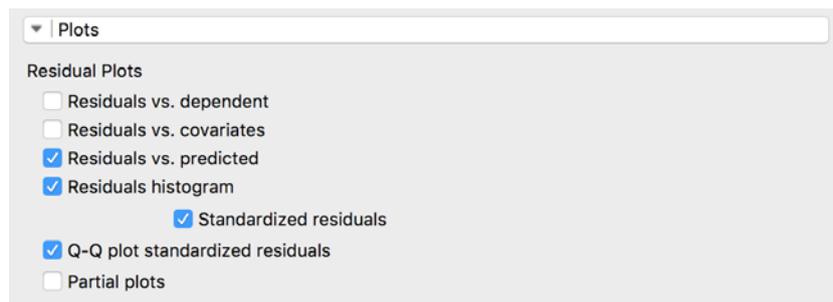

Figure III.J.18 Plots options in the Linear Regression menu

Figure III.J.19 confirms that the relationship between age and RT is linear (as could also be seen in Figure III.J.17) and the residuals do not reveal any signs of heteroscedasticity (see section 6.2 and Practical 5B, assignment 9b, for an explanation on how to interpret residual plots).
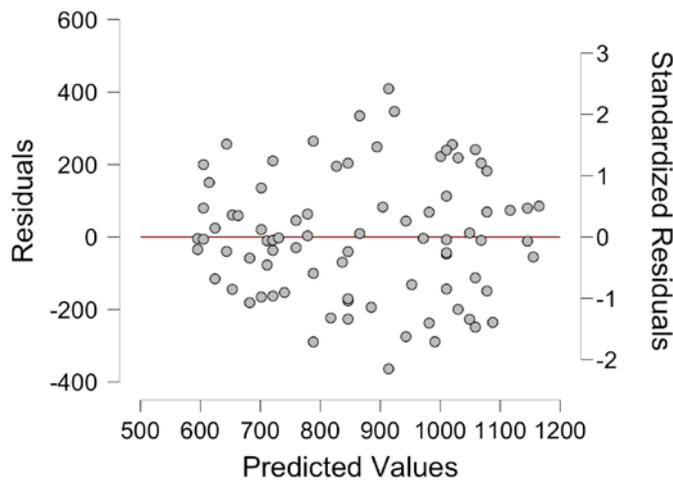
Figure III.J.19 Residual plot showing the residuals and their deviations from the predicted values.

6.3.2 Normality of the Residuals

To assess whether the model's residuals are approximately normally distributed, one can choose to create a histogram or a quantile-quantile plot (Q-Q plot) of the residuals. Both of these options can also be found under Plots, as can be seen in Figure III.J.18. The residuals histogram for the current dataset can be seen in Figure III.J.20, showing a distribution that is quite similar to a normal distribution.
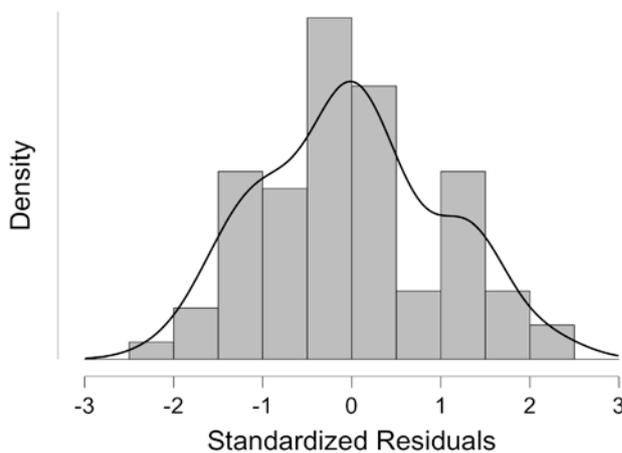

Figure III.J.20 A histogram of the residuals showing a normal distribution

The Q-Q plot in Figure III.J.21 indicates that the residuals approximate the normal distribution (see Practical 5B, assignment 9c, for an explanation on how to interpret Q-Q plots).
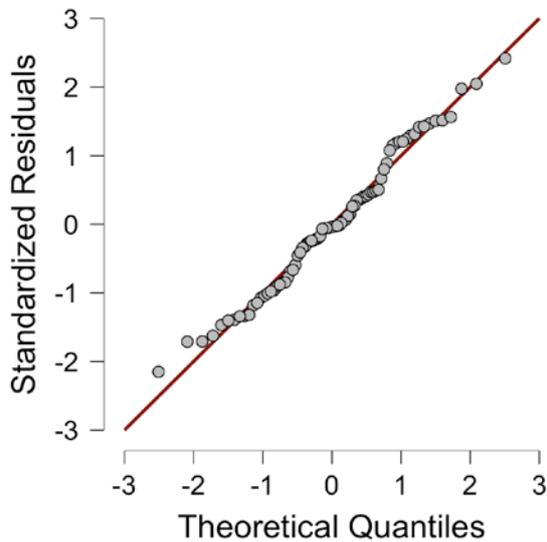
Figure III.J.21 Q-Q plot of the residuals of our model

6.4   Simple Regression: reporting the results

We suggest to report the standardized (or beta) coefficients and all associated values in the output of the third table in Table III.J.16, but include information on the model, such as the R^2 in your report (see Practical 5B, assignment 10, for details). You can use the following and Table III.J.17 as an example for your report. Alternatively you can copy the third table from the output and paste it in your report, and adapt it accordingly (Table III.J.17):

"We constructed a linear model of reaction time as a function of age. This model was significant ($F(1,80)=78.57$, $p<.001$) and explained 49.6% of the variance in the data (R-squared). Regression coefficients are shown in Table III.J.17. The positive coefficient for age reveals that, as age increases the reaction times also increase significantly. To be precise, for every added year in age, the RT increases with 9.65 milliseconds.

Table III.J.17: Regression coefficients for the linear model of reaction times as a function of age.

	Estimate (B)	Standard Error	Standardized beta (β)	t	p
(Intercept)	383.129	57.686		6.642	< .001
Age	9.649	1.089	0.704	8.864	< .001

To support your conclusion, it is common practice to also add a (reference to a) Figure visualizing the effect found, for example the scatter plot from Figure III.J.17.

7.   How To: Multiple Regression Analysis

In Part I, Section 6.3, we already discussed multiple regression with continuous variables in regression. Multiple linear regression can be used with several continuous, but also with categorical predictors. However, in JASP, there is no possibility to carry out a multiple linear regression with categorical independent variables, but only with continuous variables. To avoid unnecessary complications, we will use the same dataset as we used in 'How To Do a Simple Regression Analysis' with the only difference of an added interval/continuous independent variable. To understand this How To, we suggest you first read Chapter 6 in Part I and make sure you understand 'How to Do a Simple Regression Analysis".

7.1   Multiple Regression: opening and inspecting the data

One extra variable has been added to the data we used for the simple regression in "How to Do a Simple Regression Analysis": Caffeine. Here this refers to the number of mg caffeine per kg body weight that a participant has taken.

When we open the data in JASP, we first have a look at the data by plotting the data in scatterplots. We go to *Regression > Scatter plots* and we select the dependent variable first, and then add the independent variables. Under plots we tick the box for *Correlation matrix*. We can also tick *Statistics* under the Correlation Matrix function to get both the correlation coefficients and the scatter plots. The result can be seen in Figure III.J.22
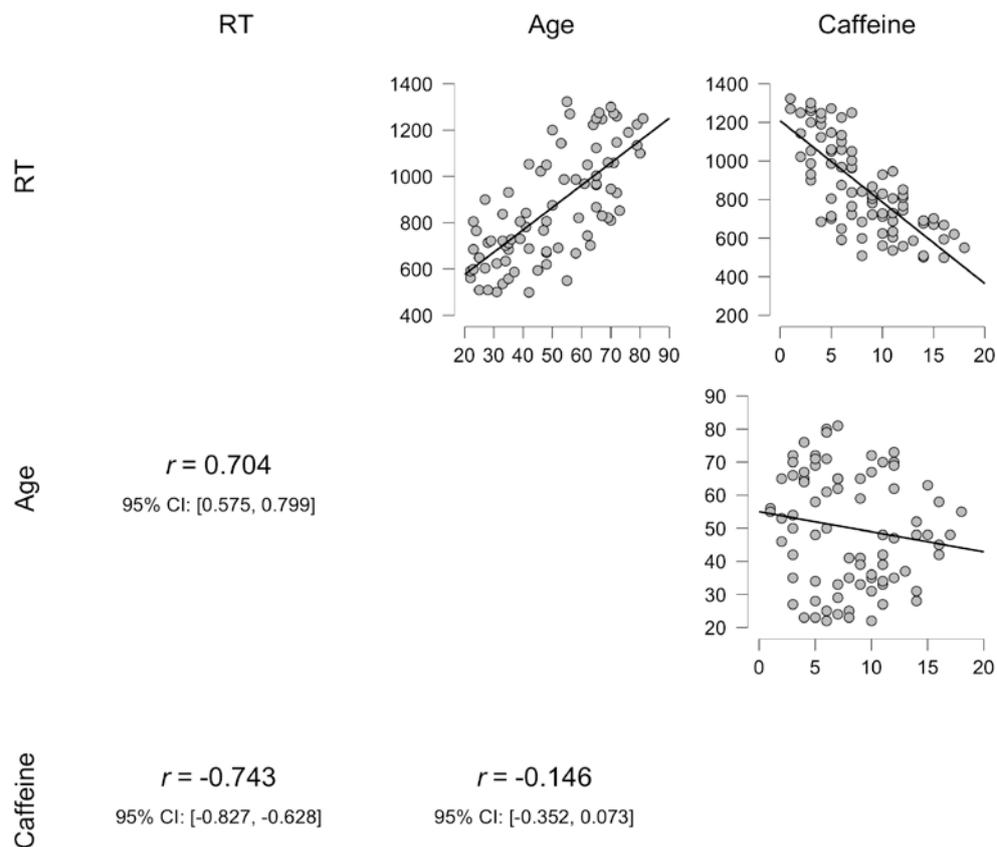
Figure III.J.22 The scatter plots of the combinations of all three variables.

The patterns in Figure III.J.22 reveal that there is a strong positive relationship between the Reaction Times (RT) in ms and the Age of the participants, as we saw in the simple regression described in "How To Do A Simple Regression Analysis". There is also a strong negative relationship of RT and the Caffeine intake. Importantly, there does not seem to be a relationship between the two independent variables (Age and Caffeine). We will come back to this later point when we discuss collinearity.

7.2 Multiple Regression: Fitting the model and interpreting the output

The way that we build the multiple regression model is the same as with the simple regression. The only difference is that we add an extra covariate, as can be seen in Figure III.J.23.
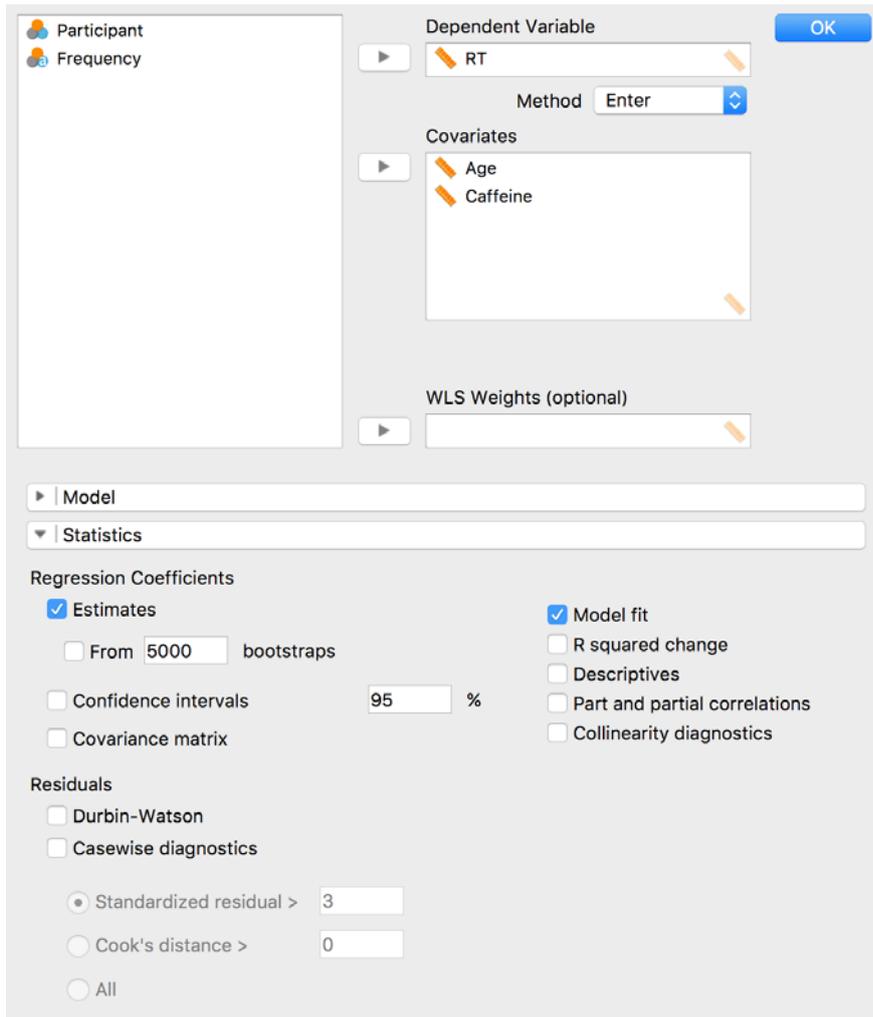
Figure III.J.23. Screenshot of the menu for the multiple linear regression

The outcome of the multiple regression analysis can be seen in Table III.J.18. As you can see, these tables are very similar to the ones in the simple regression (Table III.J.16).

Table III.J.18. Outcome tables of the Multiple regression analysis.

Model Summary

Model	R	R^2	Adjusted R^2	RMSE
1	0.956	0.914	0.912	70.59

ANOVA

Model		Sum of Squares	df	Mean Square	F	p
1	Regression	4.204e +6	2	2.102e +6	421.9	< .001
	Residual	393601	79	4982		
	Total	4.597e +6	81			

Coefficients

Model		Unstandardized	Standard Error	Standardized	t	p
1	(Intercept)	749.827	30.328		24.72	< .001
	Age	8.336	0.456	0.608	18.27	< .001
	Caffeine	−37.159	1.890	−0.654	−19.66	< .001

There is a significant positive effect of age ($p < .001$: the older, the higher or slower the RT), and a significant negative effect of caffeine ($p < .001$: the more caffeine, the lower or faster the RT). The Adjusted R^2 is 0.912, which means that 91.2% of the variance has been explained. This is a lot higher than in the simple regression analysis we did earlier. For more details on how to interpret the output of a multiple regression, see Chapter 6.3 in Part I.

There is also an option to compare this model to the simple regression model we made with only Age as a predictor variable (or covariate). To do this, you go to *Model* and select the variable you want to include in the so-called null-model. Then you select the option *R squared change* under *Statistics*, as in Figure III.J.24.
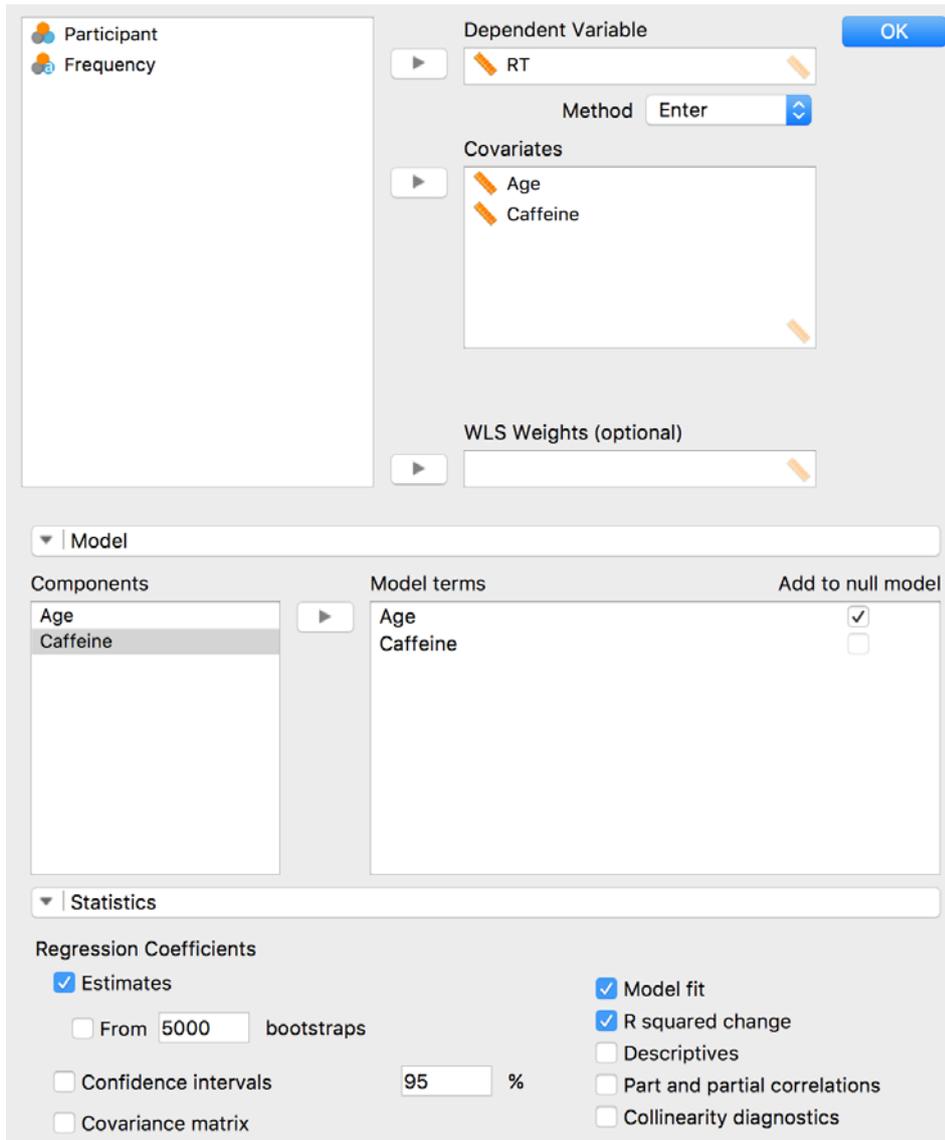
Figure III.J.24. Screenshot of how to compare two different models

In Table III.J.19 we can see the tables that are created after we select the null-model and the *R squared Change*. The *Model Summary* now shows a row for a Model 0 and one for a Model 1, the latter being the multiple regression model with our two predictor variables (age and caffeine). We can also see extra columns among which the R^2 *Change* and the *F Change*. The values on the second line of these columns show us how much the multiple regression model improved as compared to the first model. We can conclude that there is a significant improvement, which implies that the second model (multiple regression) provides a more complete analysis. The second and third table show the information we also saw in Table III.J.16 and Table III.J.18.

Table III.J.19. Comparing two Multiple Regression models.

Model Summary

Model	R	R²	Adjusted R²	RMSE	R² Change	F Change	df1	df2	p
0	0.704	0.496	0.489	170.27	0.496	78.57	1	80	< .001
1	0.956	0.914	0.912	70.59	0.419	386.51	1	79	< .001

Note. Null model includes Age

ANOVA

Model		Sum of Squares	df	Mean Square	F	p
0	Regression	2.278e +6	1	2.278e +6	78.57	< .001
	Residual	2.319e +6	80	28991		
	Total	4.597e +6	81			
1	Regression	4.204e +6	2	2.102e +6	421.86	< .001
	Residual	393601	79	4982		
	Total	4.597e +6	81			

Note. Null model includes Age

Coefficients

Model		Unstandardized	Standard Error	Standardized	t	p
0	(Intercept)	383.129	57.686		6.642	< .001
	Age	9.649	1.089	0.704	8.864	< .001
1	(Intercept)	749.827	30.328		24.724	< .001
	Age	8.336	0.456	0.608	18.273	< .001
	Caffeine	−37.159	1.890	−0.654	−19.660	< .001

7.3   Multiple Regression: Checking assumptions

Except for multicollinearity, the assumptions and how to check them are identical to those of a simple regression, so we will go through these steps relatively quickly here.
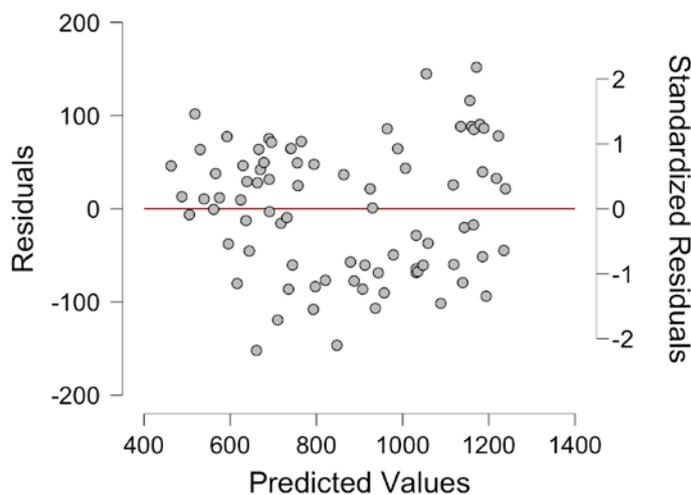We will first make a residuals plot to obtain Figure III.J.25.

Figure III.J.25. Scatter plot showing the residuals and their deviations from the predicted values

Both the relationship between Age and RT and the relationship between Caffeine and RT are linear (see also Figure III.J.22), and the residuals plot in Figure III.J.25 does not reveal any strong signs of heteroscedasticity.

The histogram of the residuals in Figure III.J.26 and the Q-Q plot in Figure III.J.27 indicate that the data follow a straight line, so it approximates the normal distribution.
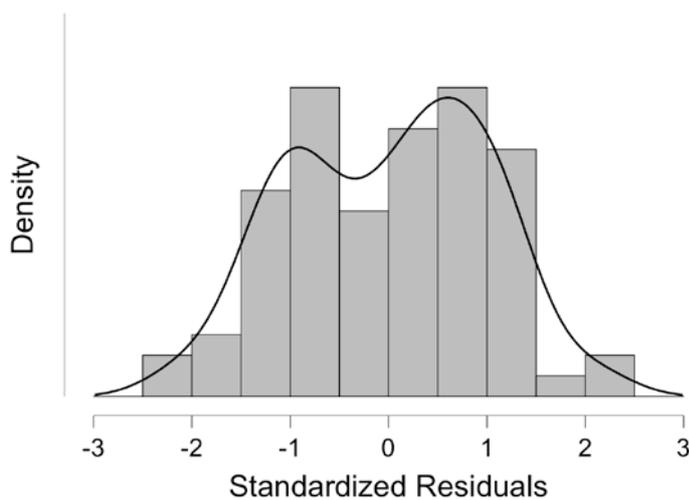

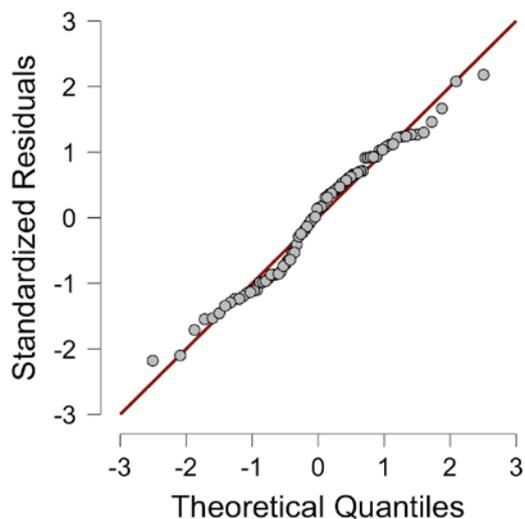
Figure III.J.26. Histogram of the residuals

Figure III.J.27. Q-Q plot of the residuals

The last thing we need to check is multicollinearity (see Section 6.4 in the book for an explanation). We already saw that there was no correlation between Age and Caffeine (see

Figure III.J.22). In addition to running a correlation, we can also check the so-called Variance Inflation (VIF) Errors by clicking on *Collinearity diagnostics* in the *Statistics*, giving us extra information in the Coefficient Table as depicted in Table III.J.20. The VIF values are below 5, so we can assume that there are no collinearity issues in this particular data set.

Table III.J.20. Coefficients Table with the Collinearity Statistics

Coefficients

Model		Unstandardized	Standard Error	Standardized	t	p	Tolerance	VIF
1	(Intercept)	749.827	30.328		24.72	< .001		
	Age	8.336	0.456	0.608	18.27	< .001	0.979	1.022
	Caffeine	−37.159	1.890	−0.654	−19.66	< .001	0.979	1.022

7.4   Multiple Regression: reporting the results

We will show a sample report for the multiple regression model that you can use as a basis for your reports. All values in the report below can be found in the output in Table III.J.18.

We constructed a linear model of reaction time as a function of age and caffeine intake. This model was significant ($F(2,79)=421.9$, $p<.001$) and explained 91% of the variance in the data (adjusted R-squared). Regression coefficients are shown in Table III.J.21. The positive coefficient for age reveals that, as age increases the reaction times also increase significantly. This pattern can also be seen in Figure III.J.22. The negative coefficient for caffeine intake indicates a faster reaction time with more caffeine intake.

Table III.J.21: Regression coefficients for the linear model of reaction times as a function of age and caffeine intake.

	Estimate (Unstandardized Beta)	SE	Standardized Beta (β)	t-value	p-value
Intercept	749.827	30.328		24.72	< .001
Age	8.336	0.456	0.608	18.27	< .001
Caffeine	-37.159	1.890	-0.654	-19.66	< .001

8.   How To: One-Way ANOVA

To show you how to perform a one-way ANOVA in R, we will be comparing three age groups and their proficiency score: younger (11-30 yrs), adult (31-50), and older (51-70) people. The important assumptions and prerequisites for the one-way ANOVA are explained Sections 4.6 and 7.2 in part I of the book.

8.1   One-way ANOVA: opening and inspecting the data

The dataset we will be using has the values 1, 2, and 3 to represent the age groups. We will first change these into the labels for the age groups, as in Figure III.J.28. If you forgot how to do this, please check Practical 1 A, assignment 3.
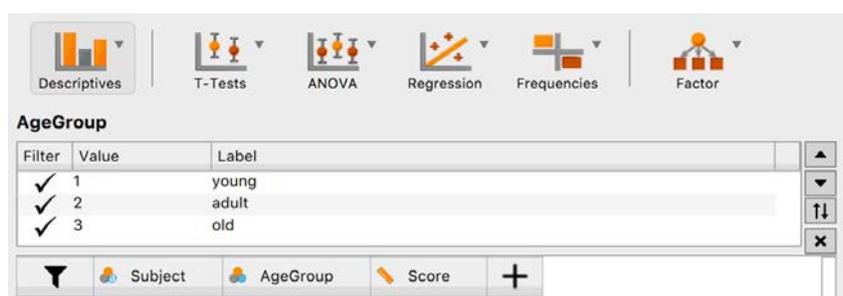

Figure III.J.28. Screenshot of changing the labels in JASP

8.2   One-way ANOVA: obtaining descriptives and creating a boxplot

Let us briefly look at some descriptives before continuing. We click on *Descriptive Statistics* under *Descriptives*, and we put Score in the *Variables* box and AgeGroup in the *Split* box (see 'How to Do Descriptives' for more information on how to do this). We then select *Boxplots* under *Plots* and the descriptives we want under *Statistics*, which gives us the descriptives table in Table III.J.22, and the Boxplot in Figure III.J.29.

Table III.J.22. Descriptives for the three age groups

Descriptive Statistics ▼

	Score		
	young	adult	old
Valid	20	20	20
Missing	0	0	0
Mean	76.35	66.35	56.10
Median	77.50	67.50	56.50
Mode [a]	88.00	54.00	49.00
Std. Deviation	10.76	9.794	14.45
Minimum	57.00	49.00	28.00
Maximum	90.00	81.00	79.00

[a] More than one mode exists, only the first is reported

Figure III.J.29. Boxplot with the dispersion of scores for young, adult, and older people

8.3 One-way ANOVA: checking assumptions

As the group sizes are smaller than 25 (see Table II.J.2 in the book for details), we will focus on the outcomes of the z-scores of both skewness and kurtosis for normality in the *Descriptive Statistics* menu (see also How to Check Assumptions). The Skewness and Kurtosis values and their standard errors can be found in Table III.J.23.

Table III.J.23. Outcomes of Skewness and Kurtosis

Descriptive Statistics

	Score		
	young	adult	old
Valid	20	20	20
Missing	0	0	0
Skewness	−0.2421	−0.1561	−0.3287
Std. Error of Skewness	0.5121	0.5121	0.5121
Kurtosis	−1.355	−1.310	−0.1761
Std. Error of Kurtosis	0.9924	0.9924	0.9924

As we divide each Skewness value by approximately 0.5), this means we need to multiply the values by approximately 2. For Kurtosis, we divide the values of Kurtosis by approximately 1. We can conclude that the values of both Skewness and Kurtosis fall within the normal range (see Practical 3A, assignment 7c, for more information).

A Shapiro-Wilk test of Normality is not really possible to carry out in JASP with nominal variables with more than two levels. An ANOVA can handle slight deviations from normality quite well, especially if the design is balanced, so we can assume here that we can continue with the ANOVA. The ANOVA does also have an option to check the Q-Q plot of the residuals. See Practical 6B, assignment 9, for more information on checking the Q-Q plot and the non-parametric alternative.

Before continuing with the ANOVA, we will check the homogeneity of variance assumption, which can be found by going to *ANOVA > ANOVA*, moving the dependent and independent variables to the respective boxes, and selecting the Homogeneity tests under Assumption Checks, as depicted in Figure III.J.30.
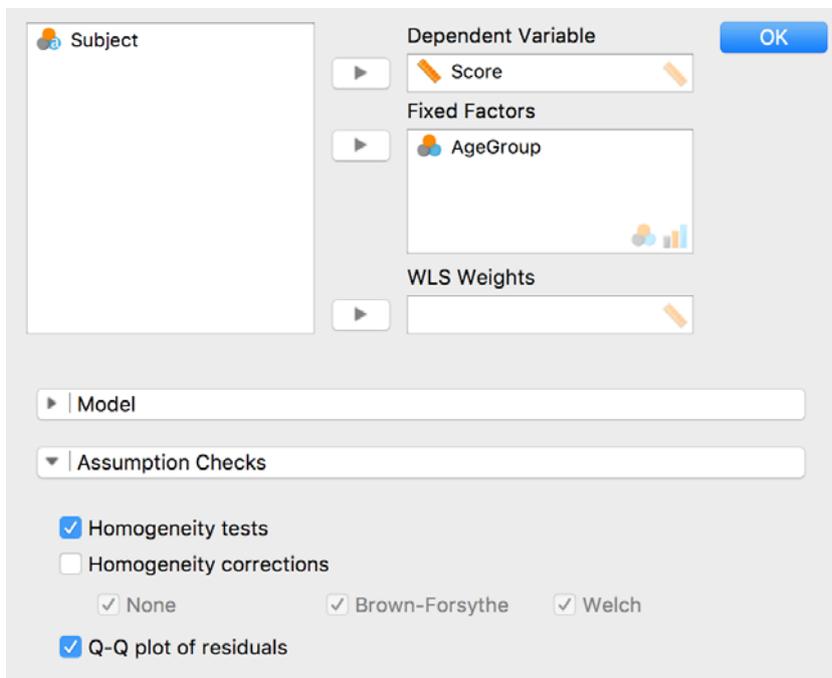

Figure III.J.30. Screenshot of changing the labels in JASP

The results of Levene's Homogeneity test can be found in Table III.J.24. The outcome shows that we can continue with the parametric one-way ANOVA (see Practical 3A, assignment 6,

for details on how to interpret Levene's output). See Practical 6B, assignment 10, for details on the non-parametric alternative in case of a violation of homogeneity.

Table III.J.24. Outcome of Homogeneity test

Test for Equality of Variances (Levene's)

F	df1	df2	p
0.386	2	57	0.681

The output also gives us the Q-Q plot of the residuals of the ANOVA model. Figure III.J.31 shows that the residuals look more or less normally distributed. See Practical 5B, assignment 9c, and Practical 6B, assignment 9, for more information on Q-Q plots.
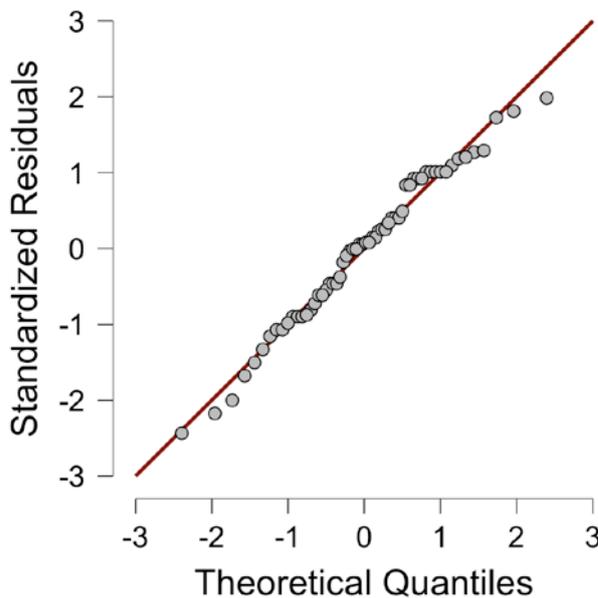

Figure III.J.31. Q-Q plot of the residuals of the ANOVA model.

8.4   One-way ANOVA: performing the test and interpreting the output

After checking the assumptions, we can carry out the ANOVA. We are already in the ANOVA menu because we checked the homogeneity of variance there. The output should also already be there in the ANOVA table, but we also want to add the effect size, which can be selected under *Additional Options*. The most common effect size is the η^2 (eta-squared), which we have selected here (For more information see Section 7.5 of part I and Practical 6B-11). The output can be seen in Table III.J.25.

Table III.J.25. Output of a One-Way ANOVA

ANOVA – Score ▼

Cases	Sum of Squares	df	Mean Square	F	p	η^2
AgeGroup	4101	2	2050.4	14.63	< .001	0.339
Residual	7991	57	140.2			

Note. Type III Sum of Squares

In this case, the results show that there are significant differences between the three different groups (see Section 7.2 for details on how to interpret ANOVA output). The effect size is 0.34, which is a large effect. We know that with a power of 0.8, we only need about 28 participants per group to get a large effect. However, the groups in this example only consist of 20 participants per group. We can therefore not conclude that we have sufficient power. We would need to check this in a program such as G*Power (Faul, Erdfelder, Lang, & Buchner, 2007) or an online Power calculator.

Of course, we still need to conduct a post hoc test and we will opt for the Tukey test (see Section 7.2 in Part I for more details), which works best with equal sample sizes and with homogeneity of variance. We can select the test under *Post Hoc Tests* in the ANOVA menu, together with checking the box for *Confidence intervals*. We will then get the table in Table III.J.26.

Table III.J.26. Output of the Post Hoc test

Post Hoc Comparisons – AgeGroup

		Mean Difference	95% CI for Mean Difference		SE	t	p_{tukey}
			Lower	Upper			
young	adult	10.00	0.990	19.01	3.744	2.671	0.026
	old	20.25	11.240	29.26	3.744	5.408	< .001
adult	old	10.25	1.240	19.26	3.744	2.738	0.022

Note. Confidence intervals based on Tukey's HSD.

The results indicate that the mean proficiency of the adult and young differs significantly (p = .026), that the old and young group differ significantly (p < .001), and also that the old and adult group differ significantly (p = .022).

Finally, you can also select a Descriptives plot with the 95% Confidence Intervals as error bars under *Descriptives Plots* in the ANOVA menu (see Figure III.J.32).
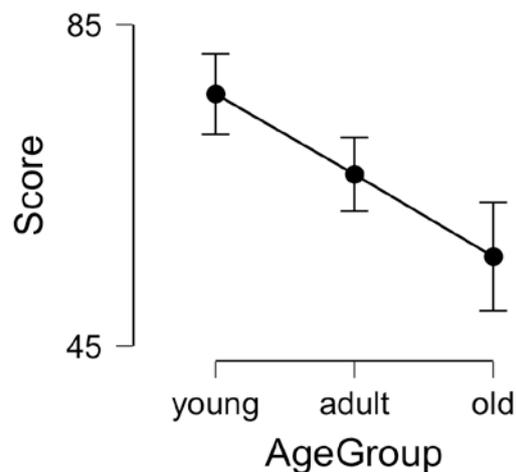
Figure III.J.32. Descriptives plot with error bars representing 95% Confidence Intervals

8.5   One-way ANOVA: reporting the results

You can use the sample format discussed in Practical 6B, assignment 13, to report the results:

There was a large significant effect of age group on proficiency scores, $F(2, 57) = 14.63$, $p < 0.001$, $\eta^2 = .34$. A Tukey post hoc analysis revealed that the youngest group performed significantly better ($M = 76.35$, $SD = 10.76$) as compared to both the middle ($M = 66.35$, $SD = 9.79$), $p = 0.03$, 95% CI [0.9, 19] and the oldest group ($M = 56.1$, $SD = 14.45$), $p < 0.001$, 95% CI [11.2, 29.3]. The middle group also did significantly better than the oldest group at $p = 0.02$, 95% CI [1.2, 19.3]. This effect is also illustrated in Figure III.J.31.

9.   How To: Factorial ANOVA

This How To will show an example of a factorial ANOVA with two independent nominal variables, so the test we will perform is a two-way ANOVA. The assumptions are the same as those for the one-way ANOVA, but note that (as also discussed in Practical 6C, assignment 6) you should check the distribution in each group or combination of groups.

As there is a lot of overlap between a one-way and a factorial ANOVA, it is advisable to read Chapter 7 of Part I first and go through the 'How To Do a One-Way ANOVA' first.

9.1   Two-way ANOVA: opening and inspecting the data

We will use example data from practical 7(f), where the question was whether encouragement (yes or no) and/or gender (boy or girl) impacted the number of marbles (interval variable) toddlers put in a vase. Remember that we are not only testing a pair of hypotheses for every IV, but also for their combined effect (also see Practical 6C, assignment 3)!

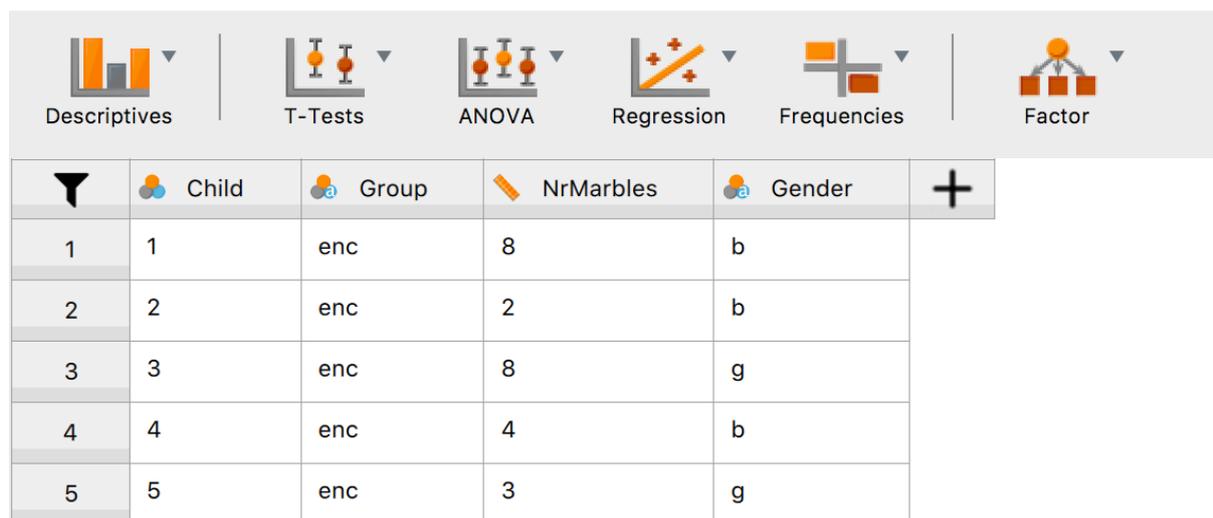The data file we will be using has the format as in Figure III.J.33.

	Descriptives	T-Tests	ANOVA	Regression	Frequencies	Factor

	Child	Group	NrMarbles	Gender	
1	1	enc	8	b	
2	2	enc	2	b	
3	3	enc	8	g	
4	4	enc	4	b	
5	5	enc	3	g	

Figure III.J.33. Data set with two independent variables

9.2   Two-way ANOVA: obtaining descriptives and checking assumptions

To plot the data, you can opt for a simple boxplot (see 'How To do Descriptives') to plot the difference between the boys and girls, and another boxplot to plot the difference between the encouraged and the not-encouraged groups. See Practical 6C, assignment 5a, for how to create a new column for the combined independent variables, yielding the descriptives in Table III.J.27 and the boxplot in Figure III.J.34.

Table III.J.27 Descriptive statistics of the 4 different groups.

Descriptive Statistics

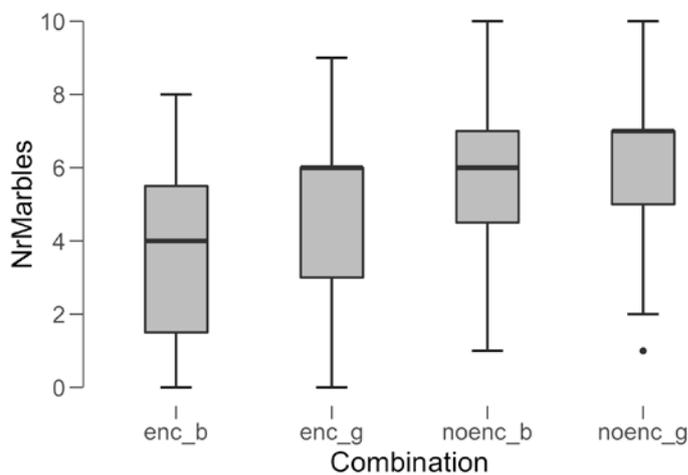|	NrMarbles			
	enc_b	enc_g	noenc_b	noenc_g
Valid	15	13	15	13
Missing	0	0	0	0
Mean	3.667	4.923	5.933	5.846
Std. Deviation	2.554	2.660	2.404	2.512
Minimum	0.000	0.000	1.000	1.000
Maximum	8.000	9.000	10.00	10.00

Figure III.J.34. Boxpot showing the number of marbles in the group of boys that was encouraged (enc_b), the group of girls that was encouraged (enc_g), the group of boys that did not receive any encouragement (noenc_b) and the group of girls that was not encouraged (noenc_g)

We will use the same column as we used for the descriptives to check normality for each combination of groups. Table III.J.28 shows the outcomes of skewness and kurtosis and the SEs associated with these values.

Table III.J.28. The values associated with skewness and kurtosis for each combination of groups

Descriptive Statistics

| | NrMarbles | | | |
	enc_b	enc_g	noenc_b	noenc_g
Valid	15	13	15	13
Missing	0	0	0	0
Skewness	0.3704	−0.1852	−0.1945	−0.5037
Std. Error of Skewness	0.5801	0.6163	0.5801	0.6163
Kurtosis	−0.8883	−0.7253	0.01252	−0.006538
Std. Error of Kurtosis	1.121	1.191	1.121	1.191

The z-scores of these values have been calculated in Table III.J.29.

Table III.J.29. Z-scores of the skewness and kurtosis for each combination of groups

	boys encouraged	girls encouraged	boys not encouraged	girls not encouraged
z-score skewness	0.64	-0.30	-0.34	-0.82
z-score kurtosis	-0.79	-0.61	0.01	-0.01

All z-score values are well within the normal range. We can therefore assume that the data of all subgroups are approximately normally distributed.

We will also have to check homogeneity of variance for the combination of all subgroups in the ANOVA menu (see How to Do a One-Way ANOVA for more information about this).

Table III.J.30. Outcome of the Levene's Test.

Test for Equality of Variances (Levene's)

F	df1	df2	p
0.227	3	52	0.877

Table III.J.30 shows that Levene's test is non-significant, suggesting that we can assume equality of variance.

9.3   Two-way ANOVA: performing the test and interpreting the output

Adding both independent variables to the *Fixed Factors* box in the *ANOVA* menu, and the dependent variable NrMarbles in the *Dependent Variable* box, gives us the outcome table of the Two-Way ANOVA. As explained in Practical 6C, assignment 7, JASP does calculate the partial η^2, but not the partial version of the ω^2. We will select both the partial η^2 and the ω^2 under Additional Options. The ANOVA table can be seen in Table III.J.31.

Table III.J.31. Output of the Factorial ANOVA

ANOVA – NrMarbles

Cases	Sum of Squares	df	Mean Square	F	p	η^2_p	ω^2
Gender	4.760	1	4.760	0.744	0.392	0.014	0.000
Group	35.429	1	35.429	5.534	0.022	0.096	0.075
Gender ∗ Group	6.286	1	6.286	0.982	0.326	0.019	0.000
Residual	332.882	52	6.402				

Note. Type III Sum of Squares

As explained in detail in Practical 6C, assignment 6, when interested in a possible interaction, you need to perform a type III ANOVA, which is the default in JASP. Table III.J.31 shows that there is a significant main effect of Group ($p = .022$). There is, however, no main effect of Gender ($p = .39$) nor is there an interaction (Group*Gender, $p= .33$) between the two variables.

As for the effect size, we've selected both the partial version of the η^2 and the omega-squared (ω^2). We will report the partial η^2 as it partials out other effects and is hence the one you need when you have multiple independent variables.

We are dealing with a medium effect of Group here. Since there was no effect of Gender nor an interaction of Gender and Group, we do not need to look at the effect size for these results (for details on how to interpret (partial) eta-squared, see Practical 6C, assignment 7).

You can also select a plot under Descriptive Plots, as in the menu in Figure III.J.35.
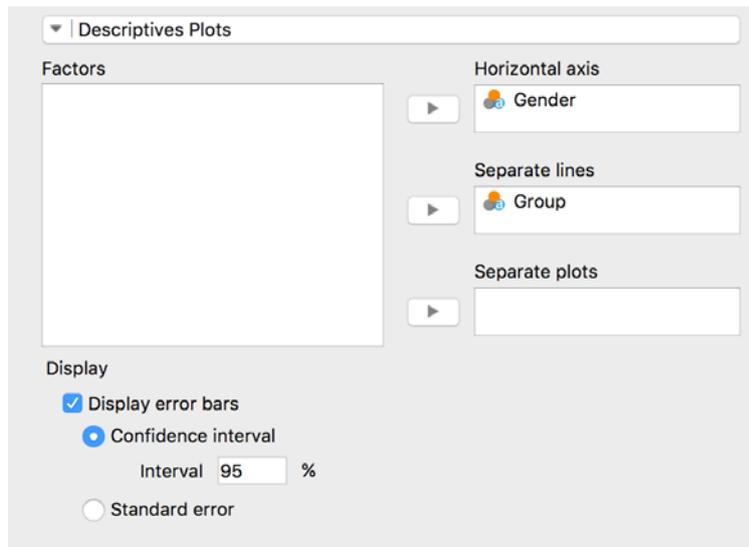
Figure III.J.35. Screenshot of the Descriptive Plots option in the ANOVA menu

You can decide to make a figure for only the main effect Group, or select both independent variables, as we have done here. This choice results in the plot that you can see in Figure III.J.36.
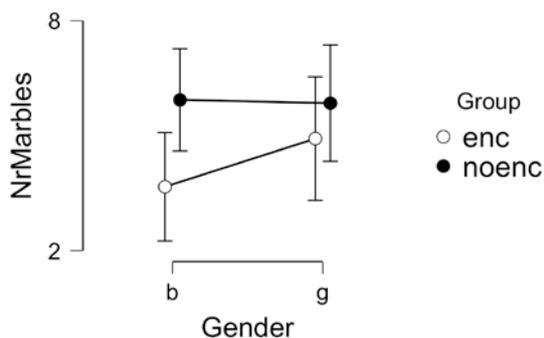

Figure III.J.36. Descriptive plot showing the main effect of group and the absence of an effect for Gender and an interaction of the two variables. Error bars represent the 95% Confidence Intervals.

9.4 Two-way ANOVA: reporting the results

We could use the following text to report on the results:

There was a significant main effect of encouragement on the number of marbles children put into the box, $F(1,52) = 5.53$, $p = 0.022$ (also see Table III.J.27 and Figure III.J.34). On average, the toddlers who were not encouraged scored higher ($M = 5.89$; $SD = 2.409$) than the toddlers who received encouragement ($M = 4.25$; $SD = 2.633$). This effect was of a medium size, $\eta^2_p = 0.096$. There was no significant difference between the boys and girls ($p = 0.39$) nor was there an interaction between gender and encouragement ($p = 0.33$).

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JASP Team (2018). JASP (Version 0.9)[Computer software]. Available at https://jasp-stats.org/