Chapter 20: Multilevel linear models

Smart Alex's Solutions

Task 1

Using the cosmetic surgery example, run the analysis described in Section 20.6.5 but also including BDI, age and gender as fixed effect predictors. What differences does including these predictors make?

Select Analyze Mixed Models ▸ Linear... (Figure 1), and specify the contextual variable by selecting **Clinic** from the list of variables and dragging it to the box labelled *Subjects* (or click on).

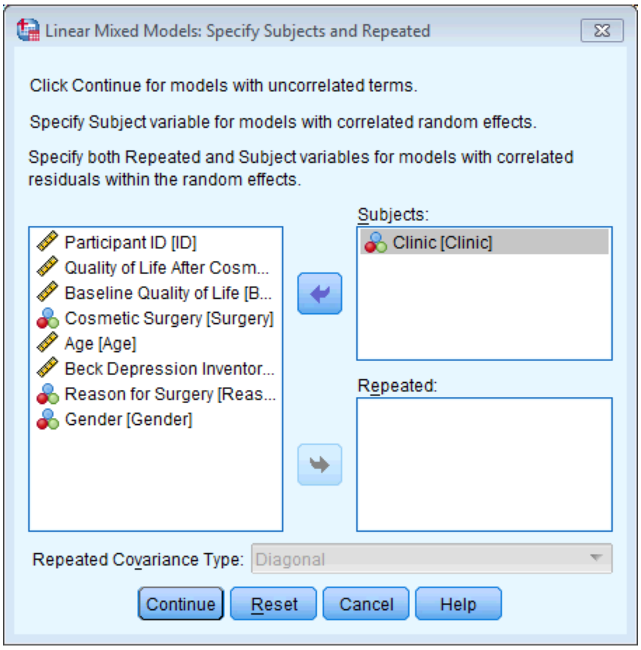

Figure 1

Click on Continue to move to the main dialog box (Figure 2). First we must specify our outcome variable, which is quality of life (QoL) after surgery, so select **Post_QoL** and drag it to the space labelled *Dependent Variable* (or click on). Next we need to specify our predictors. Therefore, select **Surgery**, **Base_QoL**, **Age**, **Gender, Reason** and **BDI** (hold down *Ctrl* and you can select all of them simultaneously) and drag them to the space labelled *Covariate(s)* (or click on)

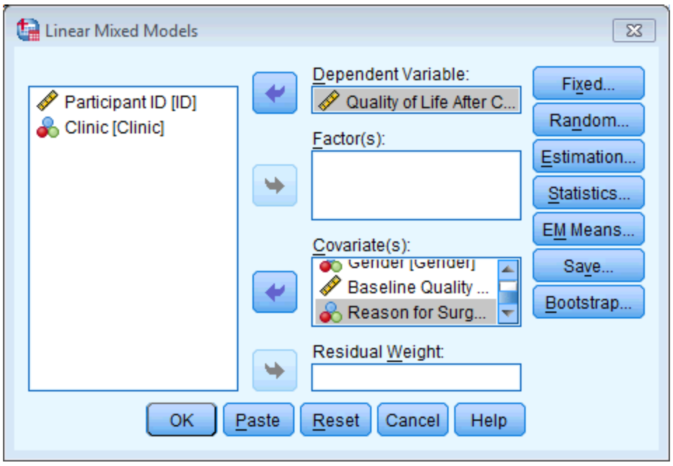

Figure 2

We need to add the predictors as fixed effect to our model, so click on Fixed..., hold down *Ctrl* and select **Base_QoL**, **Surgery**, **Age**, **Gender, Reason** and **BDI** in the list labelled *Factors and Covariates*. Then make sure that Factorial is set to Main effects and click on Add to transfer these predictors to the *Model*. To specify the interaction term, first click on Main effects and change it to Interaction (Figure 3). Next, select **Surgery** from the *Factors and Covariates* and then while holding down the *Ctrl* key select **Reason**. With both variables selected click on Add to transfer them to the *Model* as an interaction effect. Click on Continue to return to the main dialog box.

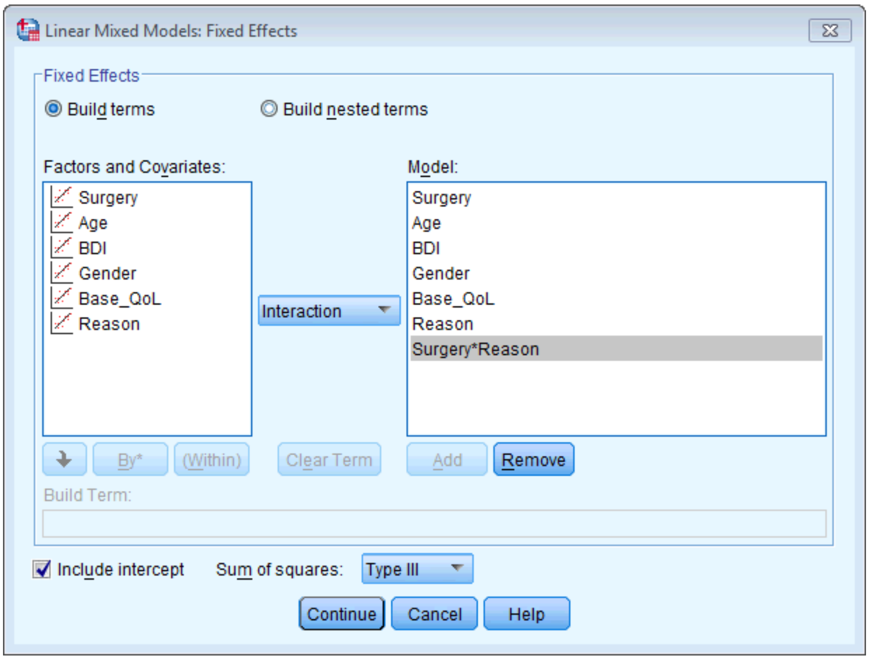

Figure 3

We now need to ask for a random intercept, and random slopes for the effect of **Surgery**. Click on Random... in the main dialog box. Select **Clinic** and drag it to the area labelled *Combinations* (or click on). We want to specify that the intercept is random, and we do this by selecting ☑ Include intercept. Next, select **Surgery** from the list of *Factors and covariates* and add it to the model by clicking on Add. The other change that we need to make is that we need to estimate the covariance between the random slope and random intercept. This estimation is achieved by clicking on Variance Components to access the drop-down list, and selecting Unstructured (Figure 4).

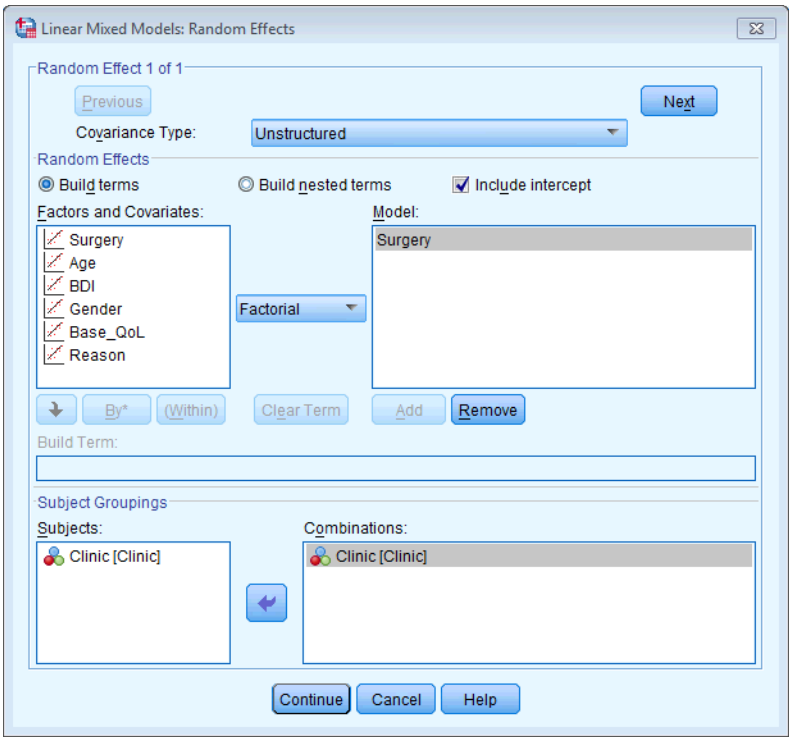

Figure 4

Click on Estimation... and select ◉ Maximum Likelihood (ML). Click on Continue to return to the main dialog box. In the main dialog box click on Statistics... and request *Parameter estimates* and *Tests for covariance parameter.* Click on Continue to return to the main dialog box. To run the analysis, click on OK. The output is as follows:

Model Dimension[a]

		Number of Levels	Covariance Structure	Number of Parameters	Subject Variables
Fixed Effects	Intercept	1		1	
	Surgery	1		1	
	Age	1		1	
	BDI	1		1	
	Gender	1		1	
	Base_QoL	1		1	
	Reason	1		1	
	Surgery * Reason	1		1	
Random Effects	Intercept + Surgery[b]	2	Unstructured	3	Clinic
Residual				1	
Total		10		12	

a. Dependent Variable: Quality of Life After Cosmetic Surgery.

b. As of version 11.5, the syntax rules for the RANDOM subcommand have changed. Your command syntax may yield results that differ from those produced by prior versions. If you are using version 11 syntax, please consult the current syntax reference guide for more information.

Output 1

Information Criteria[a]

-2 Log Likelihood	1725.385
Akaike's Information Criterion (AIC)	1749.385
Hurvich and Tsai's Criterion (AICC)	1750.572
Bozdogan's Criterion (CAIC)	1804.830
Schwarz's Bayesian Criterion (BIC)	1792.830

The information criteria are displayed in smaller-is-better forms.

a. Dependent Variable: Quality of Life After Cosmetic Surgery.

Output 2

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	123.033	66.412	.000
Base_QoL	1	272.903	20.483	.000
Surgery	1	26.301	10.474	.003
Age	1	150.834	37.321	.000
BDI	1	260.825	16.735	.000
Reason	1	253.220	1.132	.288
Gender	1	264.479	.902	.343
Surgery * Reason	1	140.835	11.809	.001

a. Dependent Variable: Quality of Life After Cosmetic Surgery.

Output 3

Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Intercept	29.753617	3.651029	123.033	8.149	.000	22.526648	36.980586
Base_QoL	.225129	.049744	272.903	4.526	.000	.127199	.323059
Surgery	-3.995719	1.234655	26.301	-3.236	.003	-6.532174	-1.459263
Age	.287954	.047135	150.834	6.109	.000	.194823	.381084
BDI	.184942	.045209	260.825	4.091	.000	.095921	.273964
Reason	1.403852	1.319315	253.220	1.064	.288	-1.194376	4.002080
Gender	-1.072721	1.129742	264.479	-.950	.343	-3.297154	1.151711
Surgery * Reason	5.021183	1.461151	140.835	3.436	.001	2.132559	7.909807

a. Dependent Variable: Quality of Life After Cosmetic Surgery.

Output 4

Estimates of Covariance Parameters[a]

Parameter		Estimate	Std. Error	Wald Z	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Residual		27.213259	2.414219	11.272	.000	22.870012	32.381333
Intercept + Surgery [subject = Clinic]	UN (1,1)	20.667649	10.598869	1.950	.051	7.564399	56.468695
	UN (2,1)	-5.415682	5.708578	-.949	.343	-16.604289	5.772926
	UN (2,2)	2.065573	3.512134	.588	.556	.073744	57.856896

a. Dependent Variable: Quality of Life After Cosmetic Surgery.

Output 5

In terms of the overall fit of this new model, we can use the log-likelihood statistics:

$$\chi^2_{\text{Change}} = 1789.05 - 1725.39 = 63.66$$

$$df_{\text{Change}} = 12 - 9 = 3$$

The critical value for the chi-square statistic (see the Appendix) is 7.81 ($p < .05$, $df = 3$); therefore, this change is significant. Including these three predictors has improved the fit of the model. **Age**, $F(1, 150.83) = 37.32$, $p < .001$, and **BDI**, $F(1, 260.83) = 16.74$, $p < .001$, significantly predicted quality of life after surgery but **Gender** did not, $F(1, 264.48) = 0.90$, $p = .34$. The main difference that including these factors has made is that the main effect of **Reason** has become non-significant, and the **Reason** × **Surgery** interaction has become more significant (its *b* has changed from 4.22, $p = .013$, to 5.02, $p = .001$).

We could break down this interaction as we did in the chapter by splitting the file and running a simpler analysis (without the interaction and the main effect of **Reason**, but including **Base_QoL**, **Surgery**, **BDI**, **Age**, and **Gender**). If you do these analyses you will get the parameter tables shown in Output 6. These tables show a similar pattern to the example in the book. For those operated on only to change their appearance, surgery significantly predicted quality of life after surgery, $b = -3.16$, $t(5.25) = -2.63$, $p = .04$. Unlike when age, gender and BDI were not included, this effect is now significant. The negative gradient shows that in these people quality of life was lower after surgery compared to the control group. However, for those who had surgery to solve a physical problem, surgery did not significantly predict quality of life, $b = 0.67$, $t(10.59) = 0.58$, $p = .57$. In essence, the inclusion of age, gender and BDI has made very little difference in this latter group. However, the slope was positive, indicating that people who had surgery scored higher on quality of life than those on the waiting list (although not significantly so!). The interaction effect, therefore, as in the chapter, reflects the difference in slopes for surgery as a predictor of quality of life in those who had surgery for physical problems (slight positive slope) and those who had surgery purely for vanity (a negative slope).

Surgery to Change Appearance

Estimates of Fixed Effects[a,b]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Intercept	28.394910	4.094489	70.622	6.935	.000	20.229974	36.559847
Base_QoL	.147062	.054159	94.007	2.715	.008	.039527	.254597
Surgery	-3.163418	1.201737	5.248	-2.632	.044	-6.209152	-.117683
Age	.198532	.058282	64.967	3.406	.001	.082133	.314931
BDI	.472556	.057825	89.035	8.172	.000	.357660	.587452
Gender	-4.696939	1.475924	83.464	-3.182	.002	-7.632250	-1.761627

a. Reason for Surgery = Change Appearance

b. Dependent Variable: Quality of Life After Cosmetic Surgery.

Surgery for a Physical Problem

Estimates of Fixed Effects[a,b]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Intercept	29.893048	4.336370	81.790	6.894	.000	21.266295	38.519802
Base_QoL	.265651	.068613	170.760	3.872	.000	.130211	.401090
Surgery	.666094	1.143140	10.594	.583	.572	-1.861760	3.193949
Age	.274837	.065504	81.130	4.196	.000	.144507	.405167
BDI	.118640	.063285	162.672	1.875	.063	-.006326	.243605
Gender	-.460960	1.476483	168.659	-.312	.755	-3.375728	2.453809

a. Reason for Surgery = Physical reason

b. Dependent Variable: Quality of Life After Cosmetic Surgery.

Output 6

Task 2

*Using our growth model example in this chapter, analyse the data but include **Gender** as an additional covariate. Does this change your conclusions?*

First, select Analyze Mixed Models ▸ Linear... and in the initial dialog box (Figure 5) set up the level 2 variable. In this example, life satisfaction at multiple time points is nested within people. Therefore, the level 2 variable is the person and this variable is represented by the variable labelled **Person**. Select this variable and drag it to the box labelled *Subjects* (or click on). Click on Continue to access the main dialog box.

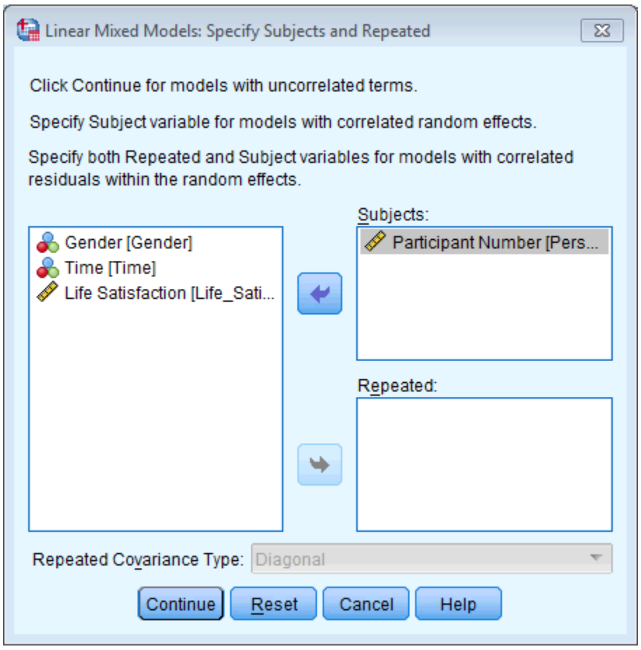

Figure 5

In the main dialog box (Figure 6) we need to set up our predictors and outcome. The outcome was life satisfaction, so select **Life_Satisfaction** and drag it to the box labelled *Dependent Variable* (or click on). Our predictor, or growth variable, is **Time**, so select this variable and drag it to the box labelled *Covariate(s)*, or click on . We also want to include **Gender**, so select this variable and drag it to the box labelled *Covariate(s)*, or click on .

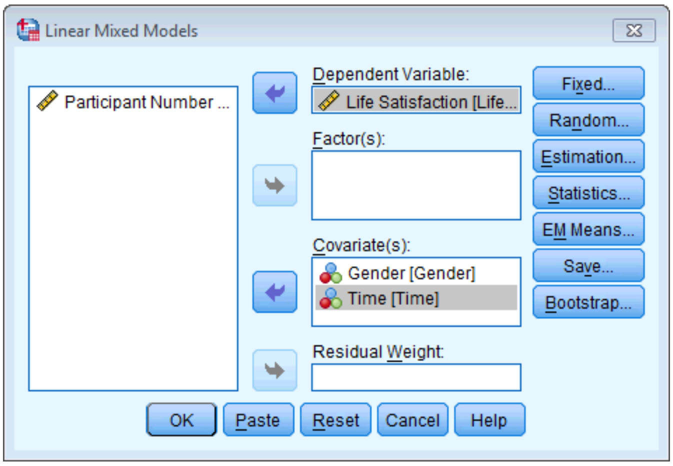

Figure 6

Click on Fixed... to bring up the fixed effects dialog box (Figure 7). First we need to include **Gender** in the model, so select this variable and click on Add to add it into the model. To specify the linear polynomial, click on **Time** and then click on Add to add it into the model. To add the higher-order polynomials we need to select Build nested terms. Select **Time** in the *Factors and Covariates* list and will become active; click on this button and **Time** will appear in the space labelled *Build Term*. For the quadratic or second-order polynomial we need to define **Time**², and we can specify this by clicking on By* to add a multiplication symbol to our term, then selecting **Time** again and clicking on ➔. The *Build Term* bar should now read *Time*Time* (or, put another way, **Time**²). Click on Add to put it into the model. Finally, let's add the cubic trend. For the cubic or third-order polynomial we need to define **Time**³ (or *Time*Time*Time*). We build this term up in the same way as for the quadratic polynomial: select **Time**, click on ➔, click on By*, select **Time** again, click on ➔, click on By* again, select **Time** for a third time, click on ➔, click on Add. This should add the third-order polynomial to the model. Click on Continue to return to the main dialog box.

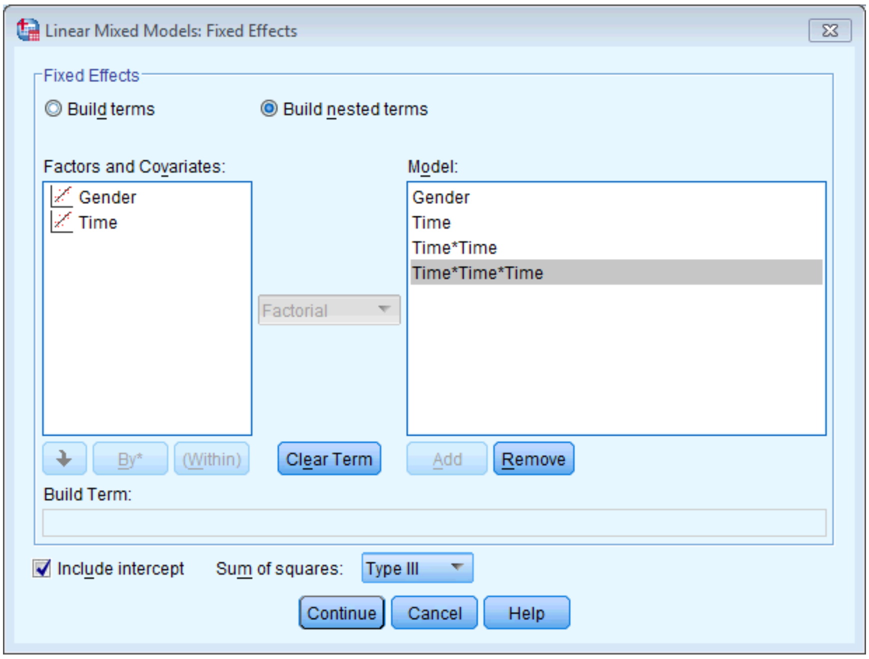

Figure 7

As in the chapter, we expect the relationship between time and life satisfaction to have both a random intercept and a random slope. We need to define these parameters now by clicking on Random... in the main dialog box. We specify our contextual variable by selecting **Person** and dragging it to the area labelled *Combinations* (or click on ➔). To specify that the intercept is random select ☑ Include intercept, and to specify random slopes for the effect of **Time**, click on this variable in the *Factors and Covariates* list and then click on Add to include it in the *Model*. Finally, we need to specify the covariance structure. As in the chapter, choose an autoregressive covariance structure, AR(1), and let's also assume that variances will be heterogeneous. Therefore, select AR(1): Heterogeneous from the drop-down list. Click on Continue to return to the main dialog box.

Click on Estimation... and select ◉ Maximum Likelihood (ML) and then click on Statistics... and select *Parameter estimates* and *Tests for covariance parameters*. Click on Continue to return to the main dialog box. To run the analysis, click on OK.

The output is the same as the last output in the chapter, except that it now includes the effect of **Gender**. To see whether **Gender** has improved the model we again compare the value of –2*LL* for this new model to the value in the previous model. We have added only one term to the model, so the new degrees of freedom will have risen by 1, from 8 to 9 (again you can find the value of 9 in the row labelled *Total* in the column labelled *Number of Parameters*, in the table called **Model Dimension**). We can compute the change in –2*LL* as a result of **Gender** by subtracting the –2*LL* for this model from the –2*LL* for the last model in the chapter:

$$\chi^2_{\text{Change}} = 1798.86 - 1798.74 = 0.12$$
$$df_{\text{Change}} = 9 - 8 = 1$$

The critical values for the chi-square statistic for $df = 1$ in the Appendix are 3.84 ($p < .05$) and 6.63 ($p < .01$); therefore, this change is not significant because 0.12 is less than the critical value of 3.84.

The table of fixed effects and the parameter estimates (Outputs 10 and 11) tell us that the linear, $F(1, 221.41) = 10.01$, $p < .01$, and quadratic, $F(1, 212.51) = 9.41$, $p < .01$, trends both significantly described the pattern of the data over time; however, the cubic trend, $F(1, 214.39) = 3.19$, $p > .05$, does not. These results are basically the same as in the chapter. Gender itself is also not significant in this table, $F(1, 113.02) = 0.11$, $p > .05$.

Output 11 also tells us about the random parameters in the model. First of all, the variance of the random intercepts was $\text{Var}(u_{0j}) = 3.90$. This suggests that we were correct to assume that life satisfaction at baseline varied significantly across people. Also, the variance of the people's slopes varied significantly $\text{Var}(u_{1j}) = 0.24$. This suggests also that the change in life satisfaction over time varied significantly across people too. Finally, the covariance between the slopes and intercepts (−0.39) suggests that as intercepts increased, the slope decreased.

These results confirm what we already know from the chapter. The trend in the data is best described by a second-order polynomial, or a quadratic trend. This reflects the initial increase in life satisfaction 6 months after finding a new partner but a subsequent reduction in life satisfaction at 12 and 18 months after the start of the relationship. The parameter estimates tell us much the same thing. As such, our conclusions have been unaffected by including gender.

Model Dimension[a]

		Number of Levels	Covariance Structure	Number of Parameters	Subject Variables
Fixed Effects	Intercept	1		1	
	Gender	1		1	
	Time	1		1	
	Time * Time	1		1	
	Time * Time * Time	1		1	
Random Effects	Intercept + Time	2	Heterogeneous First-Order Autoregressive	3	Person
Residual				1	
Total		7		9	

a. Dependent Variable: Life Satisfaction.

Output 7

Information Criteria[a]

-2 Log Likelihood	1798.744
Akaike's Information Criterion (AIC)	1816.744
Hurvich and Tsai's Criterion (AICC)	1817.165
Bozdogan's Criterion (CAIC)	1862.484
Schwarz's Bayesian Criterion (BIC)	1853.484

The information criteria are displayed in smaller-is-better forms.

a. Dependent Variable: Life Satisfaction.

Output 8

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	147.681	543.622	.000
Gender	1	113.017	.114	.736
Time	1	221.413	10.006	.002
Time * Time	1	212.508	9.403	.002
Time * Time * Time	1	214.391	3.184	.076

a. Dependent Variable: Life Satisfaction.

Output 9

Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Intercept	6.695741	.287177	147.681	23.316	.000	6.128233	7.263248
Gender	-.122985	.364312	113.017	-.338	.736	-.844752	.598782
Time	1.544366	.488237	221.413	3.163	.002	.582181	2.506552
Time * Time	-1.323256	.431531	212.508	-3.066	.002	-2.173886	-.472626
Time * Time * Time	.170194	.095374	214.391	1.784	.076	-.017796	.358184

a. Dependent Variable: Life Satisfaction.

Output 10

Estimates of Covariance Parameters[a]

Parameter		Estimate	Std. Error	Wald Z	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Residual		1.834228	.178854	10.255	.000	1.515142	2.220512
Intercept + Time [subject = Person]	Var: Intercept	3.900192	.702979	5.548	.000	2.739451	5.552754
	Var: Time	.244606	.096873	2.525	.012	.112553	.531588
	ARH1 rho	-.387545	.151208	-2.563	.010	-.639689	-.060096

a. Dependent Variable: Life Satisfaction.

Output 11

Task 3

*Hill, Abraham, and Wright, (2007) examined whether providing children with a leaflet based on the 'theory of planned behaviour' increased their exercise. There were four different interventions (**Intervention**): a control group, a leaflet, a leaflet and quiz, and a leaflet and plan. A total of 503 children from 22 different classrooms were sampled (**Classroom**). The 22 classrooms were randomly assigned to the four different conditions. Children were asked 'On average over the last three weeks, I have exercised energetically for at least 30 minutes ______ times per week' after the intervention (**Post_Exercise**). Run a multilevel model analysis on these data (**Hill et al. (2007).sav**) to see whether the* *intervention affected the children's exercise levels (the hierarchy is children within classrooms within interventions).*

A graph of the data is shown in Figure 8; the big dots are means for the schools, and the boxplots are standard boxplots, which is to say that they ignore the hierarchical structure of the data. The data file is shown in Figure 9.

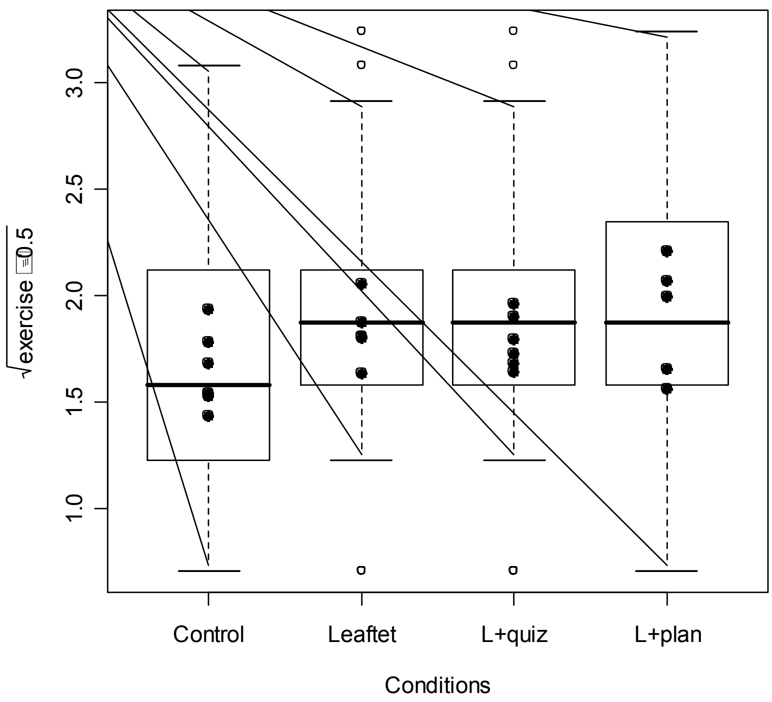

Figure 8

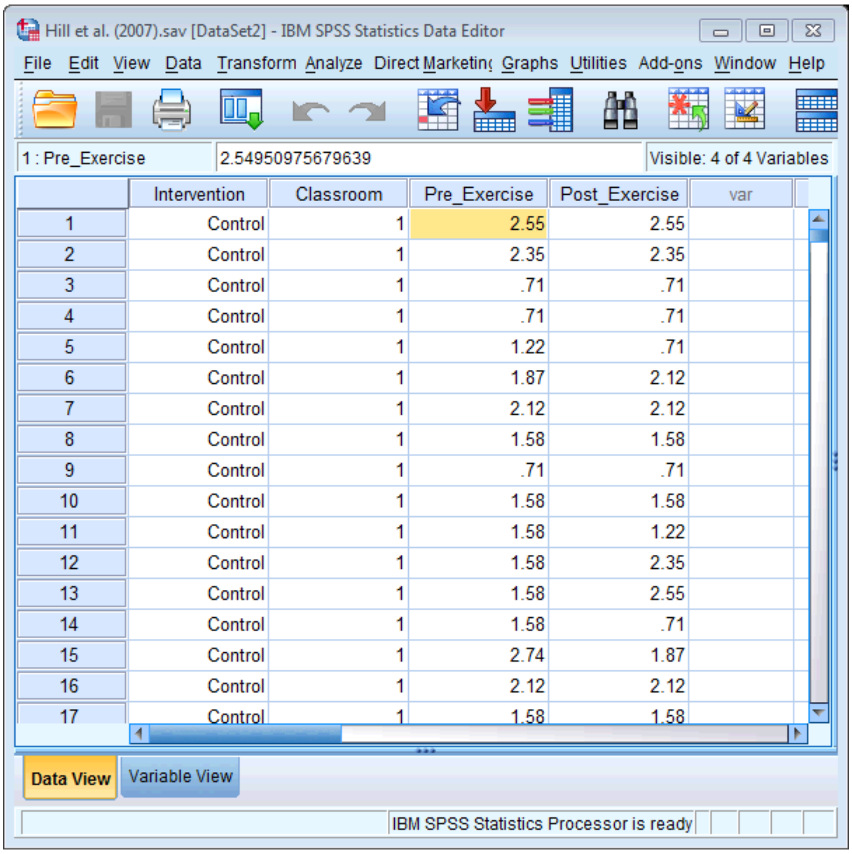

Figure 9

The analysis is done with the *mixed models* procedure by selecting Analyze Mixed Models ▸ Linear... . At the first screen (Figure 10) you enter your level 2 variable in the *Subjects* box (**Classroom**). Remember: this procedure assumes that you are doing repeated-measures analysis of individuals.

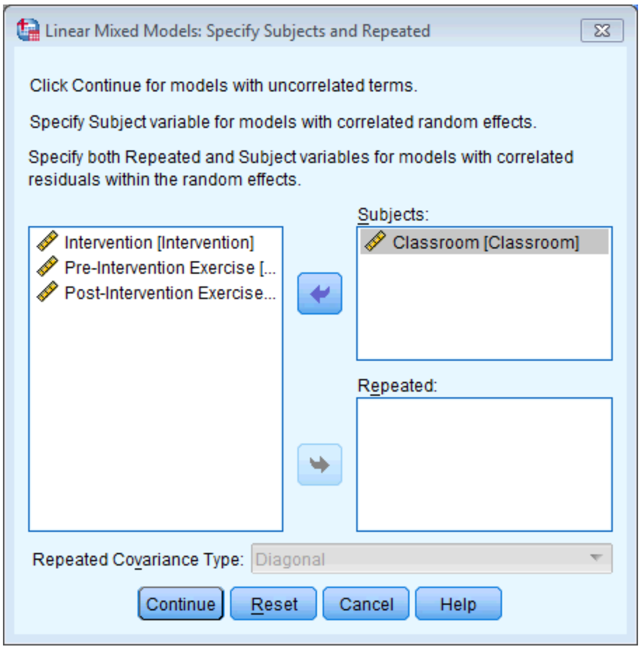

Figure 10

After clicking on Continue you enter the outcome variable (**Exercise**) and the predictor (**Intervention**).

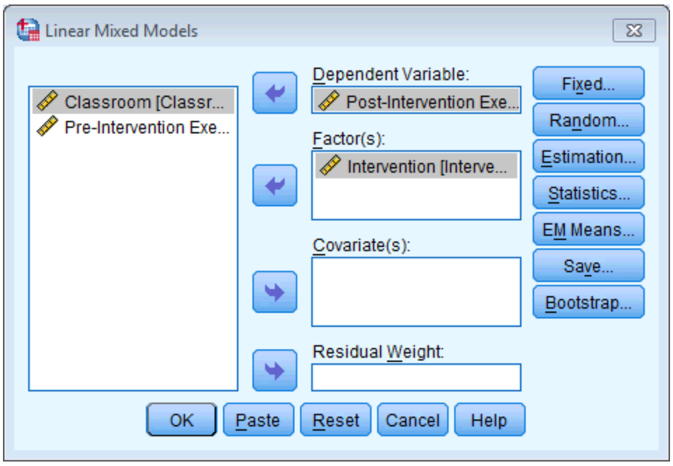

Figure 11

You then have six buttons to enter the details of the analyses. Here we consider only Fixed... and Random... . The Fixed... screen (Figure 12) allows you to enter the fixed part of the model. This is the condition the participant is in. Select the variable that specifies conditions (**Intervention**) and click on Add .

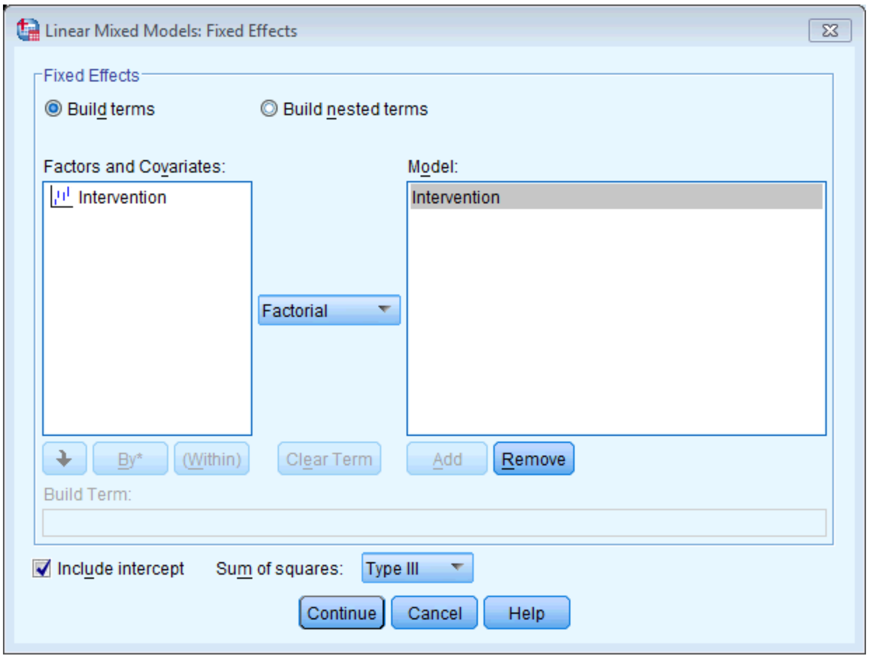

Figure 12

The Random... screen (Figure 13) is where you can really take advantage of the procedure's flexibility. The model looked at here is one of the simpler multilevel models. Highlight **Classroom** in the *Subjects* box and put it into the *Combinations* box by clicking on [arrow button]. This tells the computer that this is the cluster variable. By not entering any variables into the *Model* box the computer assumes that you just want a random intercept. The default choice of Variance Components should be used for this example.

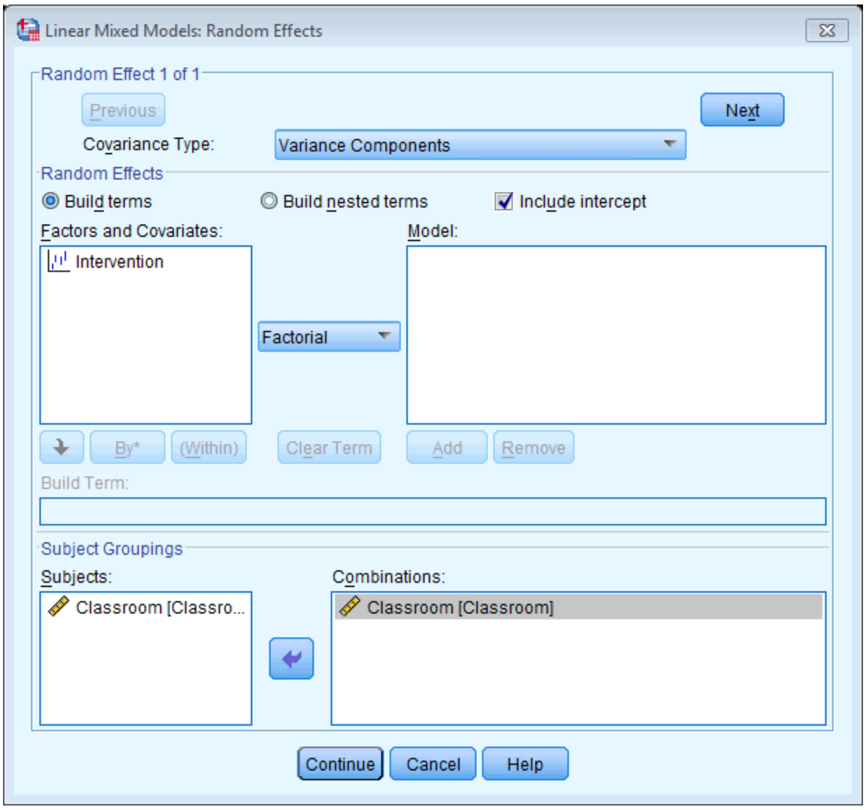

Figure 13

Now click on Statistics... and select Tests for covariance parameters (Figure 14). Click on Continue then OK.

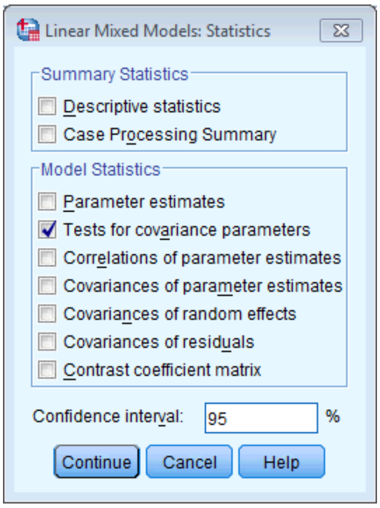

Figure 14

Model Dimension[a]

		Number of Levels	Covariance Structure	Number of Parameters	Subject Variables
Fixed Effects	Intercept	1		1	
	Intervention	4		3	
Random Effects	Intercept[b]	1	Variance Components	1	Classroom
Residual				1	
Total		6		6	

a. Dependent Variable: Post-Intervention Exercise.

b. As of version 11.5, the syntax rules for the RANDOM subcommand have changed. Your command syntax may yield results that differ from those produced by prior versions. If you are using version 11 syntax, please consult the current syntax reference guide for more information.

Output 1

Information Criteria[a]

-2 Restricted Log Likelihood	837.962
Akaike's Information Criterion (AIC)	841.962
Hurvich and Tsai's Criterion (AICC)	841.986
Bozdogan's Criterion (CAIC)	852.387
Schwarz's Bayesian Criterion (BIC)	850.387

The information criteria are displayed in smaller-is-better forms.

a. Dependent Variable: Post-Intervention Exercise.

Output 2

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	18.035	1919.366	.000
Intervention	3	18.061	1.704	.202

a. Dependent Variable: Post-Intervention Exercise.

Output 3

The first part of the output tells you details about the model that are being entered into the SPSS machinery. The *Information Criteria* box gives some of the popular methods for assessing the fit models. AIC and BIC are two of the most popular. The *Fixed Effects* box gives the information in which most of you will be most interested. It says the effect of intervention is non-significant, $F(3,18.061) = 1.704$, $p = .202$. A few words of warning: calculating a *p*-value requires assuming that the null hypothesis is true. In most of the statistical procedures covered in this book you would construct a probability distribution based on this null hypothesis, and often it is fairly simple, like the *z*- or *t*-distributions. For multilevel models the probability distribution of the null is often not known. Most packages that estimate *p*-values for multilevel models estimate this probability in complex way. This is why the denominator degrees of freedom are not whole numbers. For more complex models there is concern about the accuracy of some of these approximations. Many methodologists urge caution in rejecting hypotheses even when the observed *p*-value is less than .05.

Estimates of Covariance Parameters[a]

Parameter		Estimate	Std. Error	Wald Z	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Residual		.290766	.018745	15.511	.000	.256252	.329928
Intercept [subject = Classroom]	Variance	.023777	.012159	1.955	.051	.008727	.064782

a. Dependent Variable: Post-Intervention Exercise.

Output 4

The random effects (Output 15) show how much of the variability in responses is associated with which class a person is in: 0.023777/(0.023777 + 0.290766) = 7.56%. This is fairly small. A rough guide to whether this is greater than chance is obtained by dividing this value by its standard error to get the Wald *z* and seeing if it is greater than 1.96. It is slightly less (1.955). The significance of the Wald statistic confirms this: it just fails to reach the traditional level for statistical significance.

The result from these data could be that the condition failed to affect exercise. However, there is a lot of individual variability in the amount of exercise people get. A better approach would be to take into account the amount of self-reported exercise prior to the study as a covariate.

Task 4

*Repeat the analysis in Task 3 but include the pre-intervention exercise scores (**Pre_Exercise**) as a covariate. What difference does this make to the results?*

In the previous task, we found that there is no significant effect of the intervention on exercises levels, but we did not take into account the amount of exercise participants engaged in before the intervention. The analysis is done with the *mixed models* procedure by selecting Analyze Mixed Models ▸ Linear... . At the first screen (Figure 15) you enter your level 2 variable in the subject box (**Classroom**). Remember: this procedure assumes that you are doing repeated-measures analysis of individuals.

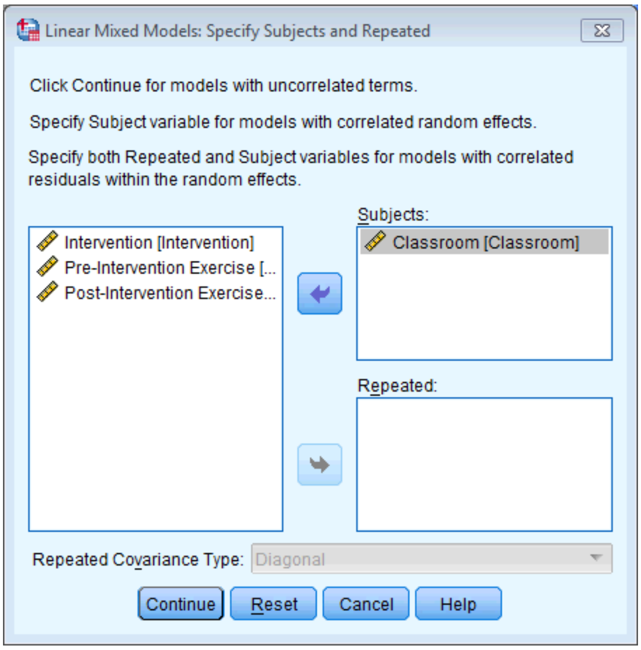

Figure 15

After clicking on Continue enter the outcome variable (**Post_Exercise**) into the *Dependent Variable* box, and the variables (**Intervention**) and (**Pre_Exercise**) into the *Covariate(s)* box (as in Figure).

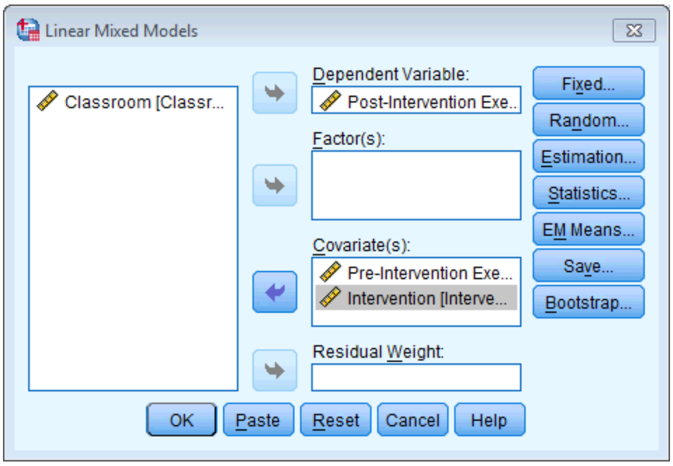

Figure 16

The Fixed... screen (Figure 17) allows you to enter the fixed part of the model. This is the condition the participant is in. Select the variables that specify conditions (**Pre_Exercise** and **Intervention**) and click on Add.

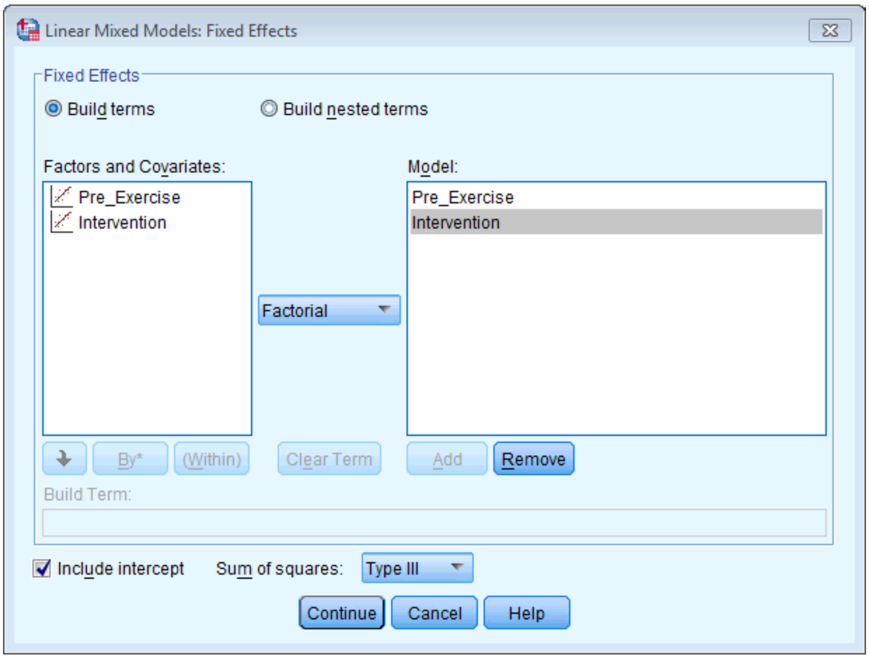

Figure 17

The Random... screen (Figure 18) is where you can really take advantage of the procedure's flexibility. The model looked at here is one of the simpler multilevel models. Highlight **Classroom** in the *Subjects* box and put it into the *Combinations* box by clicking on the arrow button. This tells the computer that this is the cluster variable. By not entering any variables into the *Model* box the computer assumes that you just want a random intercept. The default choice of Variance Components should be used for this example.

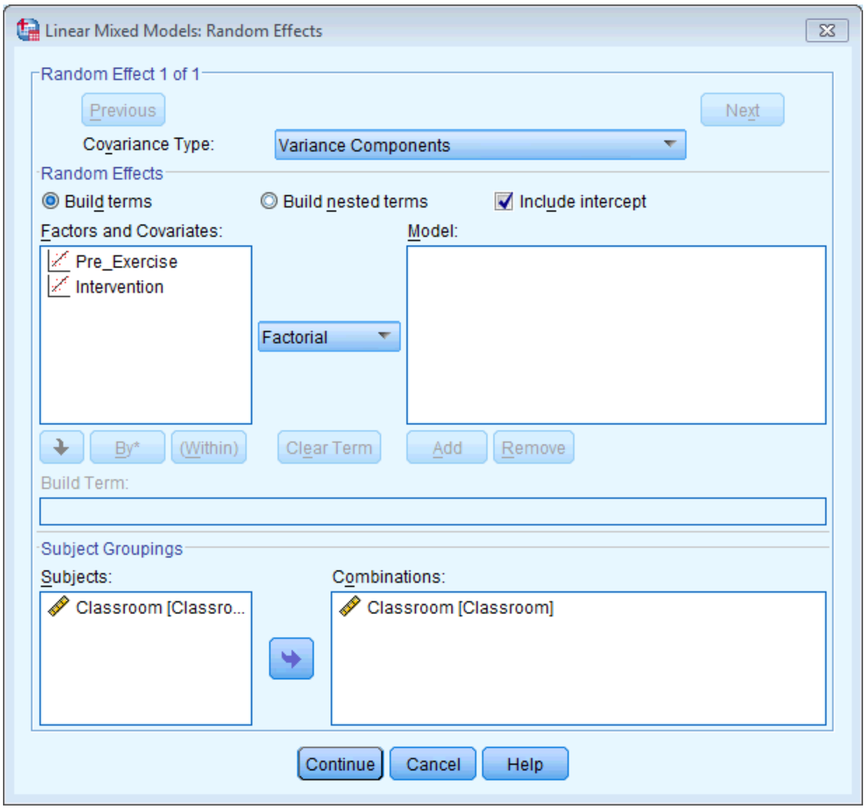

Figure 18

Now click on Statistics... and select *Tests for covariance parameters* (Figure 19). Click on Continue then OK.

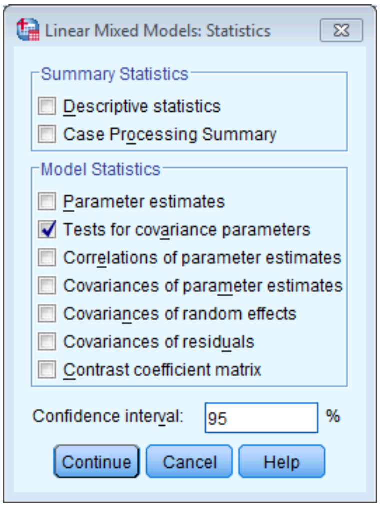

Figure 19

Model Dimension[a]

		Number of Levels	Covariance Structure	Number of Parameters	Subject Variables
Fixed Effects	Intercept	1		1	
	Pre_Exercise	1		1	
	Intervention	1		1	
Random Effects	Intercept[b]	1	Variance Components	1	Classroom
Residual				1	
Total		4		5	

a. Dependent Variable: Post-Intervention Exercise.

b. As of version 11.5, the syntax rules for the RANDOM subcommand have changed. Your command syntax may yield results that differ from those produced by prior versions. If you are using version 11 syntax, please consult the current syntax reference guide for more information.

Output 16

Information Criteria[a]

-2 Restricted Log Likelihood	397.239
Akaike's Information Criterion (AIC)	401.239
Hurvich and Tsai's Criterion (AICC)	401.263
Bozdogan's Criterion (CAIC)	411.668
Schwarz's Bayesian Criterion (BIC)	409.668

The information criteria are displayed in smaller-is-better forms.

a. Dependent Variable: Post-Intervention Exercise.

Output 17

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	59.612	37.341	.000
Pre_Exercise	1	483.504	719.775	.000
Intervention	1	21.016	15.204	.001

a. Dependent Variable: Post-Intervention Exercise.

Output 18

The first part of the output tells you details about the model that is being entered into the SPSS machinery. The *Information Criteria* box gives some of the popular methods for assessing the fit models. AIC and BIC are two of the most popular. The *Fixed Effects* box gives the information in which most of you will be most interested. It says the effect of pre-intervention exercise level is a significant predictor of post-intervention exercise level, $F(1, 483.504) = 719.775$, $p < .001$, and, most interestingly, the effect of intervention is now significant, $F(1, 21.016) = 15.204$, $p = .001$. These results show that when we take into account the amount of self-reported exercise prior to the study as a covariate, *type of intervention* becomes a significant predictor of post-intervention exercise levels.

Estimates of Covariance Parameters[a]

Parameter		Estimate	Std. Error	Wald Z	Sig.	95% Confidence Interval Lower Bound	Upper Bound
Residual		.122328	.007890	15.505	.000	.107801	.138811
Intercept [subject = Classroom]	Variance	.003946	.002917	1.352	.176	.000926	.016806

a. Dependent Variable: Post-Intervention Exercise.

Output 19

The random effects (Output 19) show how much of the variability in responses is associated with which class a person is in: 0.003946/(0.003946 + 0.122328) = 3.12%. This is pretty small. A rough guide to whether this is greater than chance is obtained by dividing this value by its standard error to get the Wald *z* and seeing if it is greater than 1.96. The current statistic is less than 1.96 (it is 1.352) and the significance of the Wald statistic confirms this, $p = .176$.