Multiple Logistic Regression – Two Categorical Independent Variables: Total GCSE Score and Placement Satisfaction

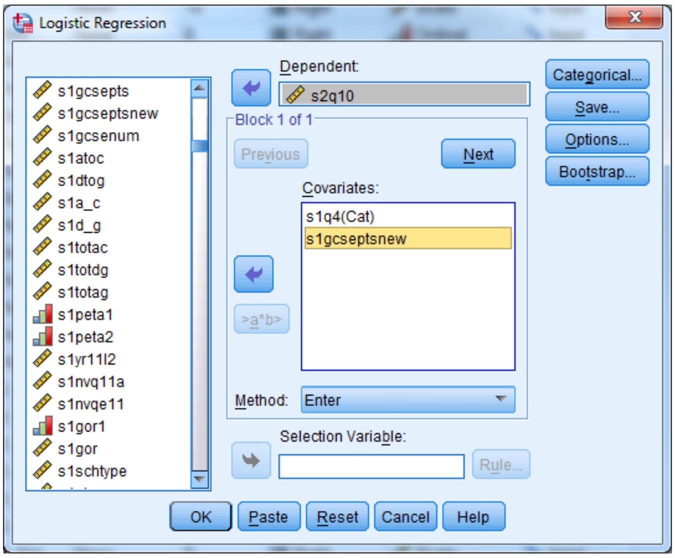
What are the odds that a young person will not be enrolled in full time education after secondary school, taking Year 11 placement satisfaction and total GCSE score into consideration?

We've seen in our two previous logistic regression models that total GCSE score in Year 11 and satisfaction with work, education, or training placement in Sweep 1 each have statistically significant relationships with full time education enrolment after secondary school. However, our previous logistic regression models explored the influence of each of our independent variables individually. Because respondent placement satisfaction in Sweep 1 may be informed by total GCSE score in Year 11, which in turn could influence enrolment in full time education, we can fit another logistic regression model, using **s2q10** (full time education enrolment) as the dependent variable and both **s1q4** (placement satisfaction) and **s1gcseptsnew** (total GCSE score) as the independent variables.

Select **Analyze**, **Regression**, and then **Binary Logistic**.

Make sure that **s2q10** is in the **Dependent** box and **s1q4(Cat)** is in the **Covariates** box. (Remember that **s1q4** is a categorical variable and we need to tell SPSS to create dummy variables for it in this model. To do so, just move **s1q4** to the **Covariates** box and click the **Categorical** button on the top right of the **Logistic Regression** dialogue box. Move **s1q4** from the **Covariates** box to the **Categorical Covariates** box and click **Continue**.)

Find **s1gcseptsnew** in the variable list on the left and add it to the **Covariates** box.



You should now see both **s1q4(Cat)** and **s1gcseptsnew** under **Covariates** in the **Logistic Regression** dialogue box.

Because we may want to be able to generalize our results to the whole of the population from which this survey data was taken (in this case, all of England), we should also calculate confidence intervals. Click on the **Options** button on the top right, and select **CI for exp(B)** under the **Statistics and Plots** header. Make sure the confidence interval is set to **95%**.

Click Continue, and then click **OK** to run the logistic regression.

Now we can look over the output of our new logistic regression model.

Case Processing Summary

Unweighted Cases[a]		N	Percent
Selected Cases	Included in Analysis	9654	68.9
	Missing Cases	4349	31.1
	Total	14003	100.0
Unselected Cases		0	.0
Total		14003	100.0

a. If weight is in effect, see classification table for the total number of cases.

S2q10 has again been coded with “Yes” as “0” and “No” as “1,” meaning that yet again, we will be predicting the odds of *not* being enrolled in full time education in Sweep 2.

Dependent Variable Encoding

Original Value	Internal Value
Yes	0
No	1

In the **Categorical Variables Codings** table below, you can see that our categorical variable, **s1q4**, have been recoded into dummy variables. **No** is again the baseline variable, just as it was in the simple logistic regression we ran with **s1q4** in the previous section. We can tell because it has not been assigned a Parameter code. This is because as the baseline, comparison variable, it won’t be included in the logistic regression model. We will need this information when we want to analyse the odds ratios.

Categorical Variables Codings

		Frequency	Parameter coding	
			(1)	(2)
S1Q4 Do you feel that you got a place in education,work or training that you wanted ?	Yes	7324	1.000	.000
	To some extent	1860	.000	1.000
	No	470	.000	.000

Again, we’ve left out the output tables for Block 0, the predictions for the logistic model excluding our two independent variables. They won’t be very informative for us. However, if you’re interested in Block 0 output, please refer to the **Simple Logistic Regression – One Continuous Variable** section.

Block 1: Method = Enter

Remember that the **Omibus Tests of Model Coefficients** output table shows the results of a chi-square test to determine whether or not placement satisfaction has a statistically significant relationship with enrolment in full time education. The Chi-square has produced a p-value of .000, making our placement satisfaction model significant at the 5% level.

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	2054.905	3	.000
	Block	2054.905	3	.000
	Model	2054.905	3	.000

Remember that we use the **Cox & Snell r^2** statistic calculated in the **Model summary** output table below to gauge how much of the variation in full time enrolment is explained by this model. In this example, the r^2 is low at 0.192. This shows that 19.2% of the variation in enrolment in full time education is explained by Sweep 1 placement satisfaction and total GCSE score in Year 11. This suggests despite our inclusion of two independent variables in this model, other factors are affecting a respondent's enrolment in full time education.

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	7349.712[a]	.192	.308

a. Estimation terminated at iteration number 5 because parameter estimates changed by less than .001.

Classification Table[a]

	Observed		Predicted: S2q10 At present are you enrolled on a full-time education course at school or college? Yes	Predicted: S2q10 At present are you enrolled on a full-time education course at school or college? No	Percentage Correct
Step 1	S2q10 At present are you enrolled on a full-time education course at school or college?	Yes	7455	359	95.4
		No	1312	528	28.7
	Overall Percentage				82.7

a. The cut value is .500

In the **Variables in the Equation** table below, we can see that the p-values for **s1gcseptsnew** and both of the dummy variables in **s1q4** are 0.000, meaning that both the variables we've included in this model have statistically significant influence on respondent enrolment in full time education.

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B) Lower	95% C.I.for EXP(B) Upper
Step 1[a]	s1q4			287.858	2	.000			
	s1q4(1)	-1.460	.111	171.656	1	.000	.232	.187	.289
	s1q4(2)	-.587	.118	24.735	1	.000	.556	.441	.701

s1gcseptsnew	-.009	.000	1067.903	1	.000	.991	.991	.992
Constant	2.999	.132	515.299	1	.000	20.061		

a. Variable(s) entered on step 1: s1q4, s1gcseptsnew.

Does this final model have a better fit than the previous two logistic regression models we created? Looking at the output in the **Model Summary** table, we can see that the Cox & Snell r^2 has risen from 0.168, its value in the simple logistic regression exploring **s2q10** and **s1gcseptsnew**, to 0.192 in this multiple logistic regression. This means that 19.2% of the variation in enrolment in full time education can be explained by this model. Therefore, this model has a better fit than our previous two simple logistic regression models.

Examining the **Block 1** output, we can see what (if anything) has changed in the predicted odds of being satisfied with Sweep 1 placement and being enrolled in full time education, now that the model controls for GCSE score. Remember that in this model, “No” was selected as our baseline comparison dummy variable and is called **s1q4** in our model outputs. Because **s1q4(1)** (with a p-value of 0.000) is a significant predictor of the odds of enrolment in full time education, we can use the odds ratio information provided for us in the **Exp(B)** column to say that a respondent who was happy with her placement in Sweep 1 has odds of not being enrolled in full time education that are 0.232 the odds of someone who was unhappy with their placement. This means that again, those happy with their placements are more likely than those who were unhappy to be enrolled in full time education. We can compare that result to 0.097, the odds ratio for a satisfied respondent not being enrolled in full time education we calculated in the previous logistic regression. Again, an odds ratio less than 1 means that the odds of an event occurring are lower in that category than the odds of the event occurring in the baseline comparison variable. An odds ratio more than 1 means that the odds of an event occurring are higher in that category than the odds of the event occurring in the baseline comparison variable. So, yet again, even controlling for the influence of GCSE score (by including it in the logistic regression model), we’ve determined that students who were satisfied with their work, education, or training in Sweep 1 are more likely to be enrolled in full time education after secondary school than are students who were not satisfied with their placements in Sweep 1.

Summary

Here, you’ve run a multiple logistic regression using s2q10 as a binary categorical dependent variable and both s1q4 and s1gcseptsnew as independent variables. Using the output of this multiple logistic regression, you predicted the odds of a survey respondent being satisfied with their Sweep 1 placement and not being enrolled in full time education, much like you did in the previous logistic regression including only s2q10 and s1q4. You were able determine how these predicted odds changed after you added s1gcseptsnew to the model and controlled for the influence of respondent GCSE score.

*****Note: as we are making changes to a dataset we’ll continue using, please make sure to save your changes before you close down SPSS. This will save you having to repeat sections you’ve already completed!**