Pre-lecture Notes II.2 – Experimental Control

Let's start with the technical (best) definition of internal validity: *the extent to which a significant IV-DV relationship is causal and not spurious*. One way to think about this is to re-code it in terms of the major threat to internal validity: the presence of one or more confounds. Thus, you can also think of internal validity, at least for experiments, as the extent to which there are no confounds or the extent to which nothing is confounded with the independent variable.

So, what's a confound? Technically, it's *an extraneous variable that changes in parallel with an independent variable*, but that also requires some unpacking. Just because some extraneous variable is not constant does not, for example, automatically make it a confound. It has to be changing in parallel with the independent variable to be a confound.

What does it mean for two variables to be changing in parallel? In general, it means that they are associated in some way, but, for present purposes, you can simplify this to mean that they are correlated, since the correlation coefficient is our favorite way (in psychology) of quantifying associations.

Some examples might help here. Assume that you are running the bright- vs. dim-lighting experiment on memory. If there is always a buzzing noise when the lights are dim and always silence when the lights are bright, then you have a perfect (minus one) correlation between brightness and noise. This would make the noises a confound.

If we now change this story such that the buzzing noise varies in strength – as opposed to being either present or absent – then it becomes a bit more complicated, but not much, as long as you think in terms of correlations. If the mean level of buzzing is higher for one lighting condition than the other, then there will be a correlation between buzzing and lighting, so buzzing will still a confound. But if the mean levels of buzzing are the same for both lighting conditions, then the correlation will be zero and buzzing is no longer a confound. In other words, you don't have to completely control the buzzing in order to avoid it becoming a confound. Having the mean level of buzzing be equal across conditions is also OK.

This brings us to what I called the **Experimental Control Hierarchy**. In general, experimental control refers to the ability of experimenters to hold everything other than the independent variable constant. In other words, experimental control is the main way that experimenters avoid and eliminate confounds. But I don't want to stop there, because this might suggest that the only good way to run an experiment is to completely control all extraneous variables, when, as the above examples aimed to show, there are other ways to avoid confounds and, therefore, maintain high internal validity. But, with that said, some ways of maintaining high internal validity are thought to be better than others. Thus, we have a hierarchy of methods, with some being preferred over others.

Note: before giving the levels of the hierarchy, it needs to be said that you apply these rules to each and every extraneous variable separately. In each case, you try to use the highest possible option in the hierarchy, but it's often the case that different extraneous variables will have to be controlled in different ways.

At the top of the hierarchy is "**hold it constant**." In this case, you do not allow the extraneous variable to change at all and it's the same value for every subject in every condition. For example, in the brightness and memory experiment, you might have a dead-silent room all the time. This is the preferred way of dealing with a potential confound, at least with regard to internal validity (as well as the other kind of validity to be stressed in this part of the course).

The second-best option is to allow the extraneous variable to vary across subjects in the experiment, but make sure that the mean value is the same for every condition; a good name for this tier of the hierarchy is "**equalize on average**." For example, you might allow the room in which the memory test is being given to vary in background noise, but you make sure that the mean noise level when the lights are bright is the same as the mean level when the lights are dim. This will ensure that there isn't a correlation between lighting and noise, so noise won't be a confound.

In an ideal world, that's the end of it. You either hold the extraneous variable constant or make it equal on average; either way, it won't be correlated with the independent variable, so it won't be a confound and won't lower your internal validity. But it isn't an ideal world and there are some potential confounds that won't let you take either of these approaches. This brings us to the third and fourth options.

> Note: these third and fourth options do not appear in any undergrad Methods text, probably because they use a form of statistics that is rather advanced. But you can understand how they work without knowing the details of the stats and you can actually use the first of these methods without knowing anything about the stats, because most stats packages will now do it for you at a click of a button (as will be demonstrated in Section). Plus, I don't want to give you the impression that not being able to either hold-it-constant or equalize-on-average means the research can't be done well (from an internal validity point-of-view), so I want you to know about these other two options.

The third-best approach to dealing with an extraneous variable is to measure it and, if it turns out to be correlated with the independent variable, somehow remove its effect on the data. This is done by the "magic" of covariance analysis. As long as the correlation between the confound and the independent variable is less than perfect (or, in practice, closer to zero than ±.70), you can subtract out the effect of the confound and see if there's anything left. We'll call this the "**measure-and-remove**" method.

Finally, the last-ditch approach is one that can be used in some situations with perfect confounds. In some cases, while you can't manipulate the variable of interest without also changing something else (creating a confound and, therefore, an experiment with very low internal validity), you can manipulate the variable that is not of interest while holding the variable of interest constant (or equal on average). This latter experiment is called a ***control experiment***. By running this control experiment, you get an idea of how much of an effect the confound (from the original experiment) might have had on the data. Then, using a much more complicated analysis than mere covariance, you subtract the effect of the confound in the control experiment from the results of the main experiment and whatever is left is the effect of variable of interest. It's like "measure-and-remove" but the measuring is done in a separate experiment, so I'll call this the "**control-experiment**" method.