Hypothesis101_LaurenWollman

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LAUREN F. WOLLMAN: Hypotheses 101 and other social science concepts by Lauren F. Wollman, PhD. One of the principal outcomes of a lit review is a clearer sense of how you, the researcher, can engage the discourse and what you can contribute to the literature. No matter how your research is designed with regard to method, you'll conduct your project through a lens unique to you-- your experiences, knowledge base, preconceptions, expectations, and other factors-- all of which contribute to what is formally known as theoretical sensitivity or experimenter bias.

In the realm of scientific experiments, bias is a decidedly evil thing. It can taint selection, skew results, and ruin or discredit entire projects. In the social sciences and the humanities, the role of value judgment on bias is much more ambivalent. Certainly, in policy work it's inescapable, but in ways that make your inquiry possible since they're a direct result or function of those very things that determine your perspective, your bias.

This is not to say that bias affords us permissiveness or intellectual laxity. To the contrary, the onus to identify and account for bias is even heavier among scholars of less clear cut, formulaic methods and disciplines. Because the consumers of policy research cannot replicate your experiments in a Petri dish or lab, and because researchers cannot deal in quantitative units of thought, we must rely on standards of credibility based on such things as transparency and precision in the identification of our biases.

Such biases though are often the basis for our best ideas. They are the fertile ground from which hunches and then hypotheses are grown, and the material from which the most compelling, persuasive arguments are woven. Just as the researcher's obligation is to disclaim the limits and influences of one's research, so the most skillful and successful thinkers and writers use those same biases to maximum benefit, use them as a springboard and as a guide.

In order to do that, you must first be familiar with the basic lexicon of social scientific inquiry. Reach all the way back to eighth grade science class. Don't hurt yourself.

Nestled back there is a dusty formula for the scientific method. One, ask a question. Two, do background research. Three, construct a hypothesis. Four, test your hypothesis. Five, analyze your results and draw a conclusion. Six, write up your results.

If you're conducting an inquiry based in the social sciences or humanities, for example, sociology, criminology, history, political science, or international relations, that scientific method is still a good sequence in so far as progression and basic steps are concerned. But policy research often concerns wicked problems in which the problem is unclear as to nature or cause, where there is no one right answer and variables are tangled, where hypotheses might or might not be testable, nor results replicable. Even if this is the case, it's often helpful to think about your research project as if it were more concrete and linear using the language of hard science as a way to move through your inquiry as systematically as possible.

You won't be able to do very much in research unless you know how to talk about variables. A variable is any entity that can take on different values. OK. So what does that mean? Anything that can vary can be considered a variable. For instance, age can be considered a variable because age can take different values for different people or for the same person at different times. Similarly, country can be considered a variable because a person's country can be assigned a value.

Variables aren't always quantitative or numerical. The variable gender consists of two text values-- male and female. We can, if it is useful, assign quantitative values instead of or in place of the text values, but we don't have to assign numbers in order for something to be a variable.

It's also important to realize that variables aren't only things that we measure in the traditional sense. For instance, in much social research and in program evaluation, we consider the treatment or program to be made up of one or more variables. In other words, the cause can be considered a variable. An educational program can have varying amounts of time on task, classroom settings, student teacher ratios, and so on. So even the program can be considered a variable, which can be made up of a number of subvariables.

An attribute is a specific value on a variable. For instance, the variable sex or gender has two attributes-- male and female. Or the variable agreement might be defined as having five attributes-- strongly disagree disagree, neutral, agree, strongly agree.

Another important distinction having to do with the term variable is the distinction between an independent and dependent variable. This distinction is particularly relevant when you are investigating cause and effect relationships. The independent variable is what you or nature manipulates-- a policy or program, or cause. The dependent variable is what is affected by the independent variable-- your effects, or outcomes. For example, if you're studying the effects of a new drug on cancer growth, the drug is the independent variable. And your measures of growth are the dependent ones.

Finally, there are two traits of variables that should always be achieved. Each variable should be exhaustive. It should include all possible answerable responses. For instance, if the variable is religion, and the only options are Protestant, Jewish, and Muslim, there are quite a few religions that haven't been included. The list does not exhaust all possibilities. On the other hand, if you exhaust all the possibilities with some variables, religion being one of them, you would simply have too many responses. The way to deal with this is to explicitly list the most common attributes and then use a general category, like other, to account for all remaining ones.

In addition to being exhaustive, the attributes of a variable should be mutually exclusive. No respondent should be able to have two attributes simultaneously. While this might seem obvious, it's often rather tricky in practice. For instance, you might be tempted to represent the variable employment status with the two attributes employed and unemployed, but these attributes are not necessarily mutually exclusive. A person who's looking for a second job while employed would be able to check both attributes.

But don't we often use questions on surveys that ask the respondent to check all that apply, and then list a series of categories? Yes, we do. But technically speaking, each of the categories in a question like that is its own variable and is treated dichotomously as either checked or unchecked-- attributes that are mutually exclusive.

Relationships-- a relationship refers to the correspondence between two variables. When we talk about types of relationships, we can mean that in at least two ways-- the nature of the relationship or the pattern of it. The nature of a relationship-- while all relationships describe the correspondence between two variables, there's a special type of relationship that holds that the two variables are not only in correspondence, but that one causes the other. This is the key distinction between a simple correlational relationship and the causal relationship.

A correlational relationship simply says that two things perform in a synchronized manner. For instance, there's often been talk of a relationship between ability in math and proficiency in music. In general, people who are put in one may have a greater tendency to be good in the other. Those who are poor in one may also tend to be poor in the other. If this relationship is true, then we can say that the two variables are correlated.

But knowing that two variables are correlated does not tell us whether one causes the other. We know, for instance, that there is a correlation between the number of roads built in Europe and the number of children born in the United States. Does that mean that if we want fewer children in the US, we should stop building so many roads in Europe? Or does it mean that if we don't have enough roads in Europe, we should encourage US citizens to have more babies? Of course not. While there is a relationship between the number of roads built and the number of babies, we don't believe that the relationship is a causal one.

This leads to consideration of what is often termed the third variable problem. In this example, it may be that there is a third variable that is causing both the building of roads and the birth rate that is causing the correlation we observe. For instance, perhaps the general world economy is responsible for both. When the economy is good, more roads are built in Europe and more children are born in the US. The key lesson here is that you have to be careful when you interpret correlations.

If you observe a correlation between the number of hours students use the computer to study and their grade point averages, with high computer users getting higher grades, you cannot assume that the relationship is causal, that computer use improves grades. In this case, the third variable might be socioeconomic status. Richer students, who have greater resources at their disposal, tend to both use computers and do better in their grades. It's the resources that drive both use and grades, not computer use that causes the change in the grade point average.

Patterns of relationships-- we have several terms to describe the major different types of patterns one might find in a relationship. First, there is the case of no relationship at all. If you know the values on one variable, you don't know anything about the values on the other. For instance, I suspect that there is no relationship between the length of the lifeline on your hand and your grade point average. If I know your GPA, I don't have any idea how long your lifeline is.

Then we have the positive relationship. In a positive relationship, high values on one variable are associated with high values on the other. And low values on one are associated with low values on the other. In this example, we assume an idealized positive relationship between years of education and the salary one might expect to be making.

On the other hand, a negative relationship implies that high values on one variable are associated with low values on the other. This is also sometimes termed an inverse relationship. Here, we show an idealized negative relationship between a measure of self-esteem and a measure of paranoia in psychiatric patients.

These are the simplest types of relationships we might typically estimate in research, but the pattern of a relationship can be more complex than this. For instance, a curvilinear relationship shows a relationship that changes over the range of both variables. In this example, the horizontal axis represents dosage of a drug for an illness and the vertical axis represents a severity of illness measure. As dosage rises, severity of illness goes down. But at some point, the patient begins to experience negative side effects associated with too high a dosage and the severity of illness begins to increase again.

Hypotheses-- a hypothesis is a specific statement of prediction. It describes in concrete rather than theoretical terms what you expect will happen in your study. Not all studies have hypotheses. Sometimes a study is designed to be exploratory-- inductive research. There is no formal hypothesis and perhaps the purpose of the study is to explore some area more thoroughly in order to develop some specific hypothesis or prediction that can be tested in future research.

A single study may have one or many hypotheses. Actually, whenever I talk about a hypothesis, I'm really thinking simultaneously about two hypotheses. Let's say that you predict there will be a relationship between two variables in your study. The way we would formally set up the hypothesis test is to formulate two hypothesis statements, one that describes your prediction and one that describes all the other possible outcomes with respect to the hypothesized relationship. Your prediction is that Variable A and Variable B will be related. And you don't care whether it's a positive or negative relationship. Then the only other possible outcome would be that Variable A and Variable B are not related.

Usually, we call the hypothesis that you support your prediction, the alternative hypothesis. And we call the hypothesis that describes the remaining possible outcomes the null hypothesis. Sometimes we use a notation like H sub A or H sub one to represent the alternative hypothesis, or your prediction, and H sub zero or H sub O to represent the null case.

You have to be careful here, though. In some studies, your prediction might very well be that there will be no difference or change. In this case, you're essentially trying to find support for the null hypothesis and you're opposed to the alternative.

If your prediction specifies a direction and the null therefore is the no difference prediction, and the prediction of the opposite direction, we call this a one-tailed hypothesis. For instance, let's imagine that you're investigating the effects of a new employee training program. And you believe one of the outcomes will be that there will be less employee absenteeism.

Your two hypotheses might be stated something like this. The null hypothesis for this study is-- as a result of the XYZ Company employee training program, there will either be no significant difference in employee absenteeism or there will be a significant increase, which is tested against the alternative hypothesis that as a result of the XYZ Company employee training program, there will be a significant decrease in employee absenteeism.

The alternative hypothesis is your prediction that the program will decrease absenteeism. The null must account for the other two possible conditions-- no difference or an increase in absenteeism. The figure shows a hypothetical distribution of absenteeism differences. We can see that the term one-tailed refers to the tail of the distribution on the outcome variable.

When your prediction does not specify a direction, we say you have a two-tailed hypothesis. For instance, let's assume you're studying a new drug treatment for depression. The drug has gone through some initial animal trials, but has not yet been tested on humans. You believe, based on theory and the previous research, that the drug will have an effect, but you're not confident enough to hypothesize a direction and say the drug will reduce depression.

SPEAKER: Yippee.

LAUREN F. WOLLMAN: After all, you've seen more than enough promising drug treatments come along that eventually were shown to have severe side effects that actually worsened symptoms. In this case, you might state the two hypotheses like this. The null hypothesis for this study is that as a result of 30 milligrams a day of the ABC drug, there will be no significant difference in depression, which is tested against the alternative hypothesis that as a result of 30 milligrams a day of the ABC drug, there will be a significant difference in depression.

Let's see how this might be applied to a homeland security related inquiry. Suppose you were interested in figuring out what causes terrorism. You would submerge yourself in the literature and find an argument running through several high profile scholars' work that poverty causes terrorism. And that claim is either appealing to you, it makes sense in the context of your own work, or you just want to test it further to see if it bears out.

So the research question is, what causes terrorism? The hypothesis is, poverty causes terrorism. Prediction-- if this is true, then where there's more poverty, there's more terrorism.

The way this is represented in algebraic and logical symbology is like this. If A, then B, where A, poverty, is the independent variable and B, terrorism, is the dependent variable. This connotes a directly proportional symmetric equivalence. If poverty increases, then so does terrorism.

How could you test this? Obviously, not physically, empirically, clinically. For ethical as well as logistical reasons, you can't go around fiddling with poverty levels just to see what will happen. So for most policy work, the tests are abstract on paper.

Already, there is a problem. How do we define poverty? This will obviously determine the kinds and amount of data we can work with-- income per capita, GDP-- you as the researcher must decide the most accurate, most relevant definition or measure of poverty and be explicit and transparent with it.

If your reader disagrees with that definition, or asks what would happen if another were substituted, the experiment can be replicated with slightly different variables. This is, in fact, the substance of many scholarly debates where policy work is concerned-- debate over the definition and employment of terms.

GDP is problematic here because it disguises regional variances in both wealth and potentially in unrest. You could also have a high GDP in a country with very poor people in it. Per capita is a rough average, too, of an entire country. And if we're looking at terrorism within countries, the terminology is too broad, too inclusive. Maybe you want a more basic definition, or maybe a more specific one. But clearly figuring out the accurate and relevant measure is critical to the larger experiment.

We now move to the same challenges with poverty. How are you defining drawing the parameters of terrorism? You will probably go back to the literature to identify the most commonly used versions of that word and the implications and distinctions of using each. Whichever one you go with, you should think through the ramifications of your experiment if one is substituted for another. In other words, how generalizable your findings or logic are versus how limited by the specific variable scope.

Let's say you've settled the terminological and scoping questions, and you've done a little work on this hypothesis. What you would find, in fact, is that there is no correlation between poverty and terrorism. The poorest countries do not have the highest rates or incidence of indigenous terrorism. And the countries with the most terrorists are not the poorest. That conclusion, of course, presumes a certain use of those words. I had to add indigenous as part of my definitions in order to even be able to look at those two dynamics in operation together.

But let's say that this outcome does not look right to me. I still really suspect that the two phenomena are somehow related. Then I would go back and look at my definitions, as well as my data set. Maybe I was looking too broadly, maybe too narrowly.

Maybe it turns out that poverty is a condition variable. It is necessary but not itself sufficient to support terrorism. It must be present, but must be accompanied by other conditions or intervening variables, for example, ideological instability, religious conflict, and so forth. Maybe it turns out that terrorism is really five different phenomena, the way cancer is really a whole constellation of diseases, and that poverty does cause one of those types of terrorism.

The best you can hope for with this kind of policy work is really correlation rather than cause, probability rather than proof. There are two simple reasons for this. In studies where you have a large number of data points, we call it large N. You can use statistical analysis to sort through patterns. Statistics will tell you what's related, but not in what way. They'll not isolate causation.

On the other hand, if you have only a few data points, which we call small n, you can't use statistical analysis, but you can use case study methodologies. And although you might be able to identify pretty confidently that poverty caused terrorism in one or two cases, you would not be able to generalize those results. You would not be able to say that A causes B all the time or even under what conditions because you have no idea what variables were relevant in your few cases.

We've seen that the principles and rules of scientific experimentation are much trickier to apply in the realms of social and policy research. In the realms of critical and grounded theory, humanities research, and many other disciplinary approaches to homeland security, the relevance is even more tenuous and the applicability even shakier. If you're doing certain kinds of research in the unknown quadrants, for example, you're probably not dealing in variables, cases, data sets, or statistics at all. Maybe you're just operating in the realms of theory and ideas.

Those certainly have their own sets of rules, terminology, and common practice, but the principles governing the construction and testing of hypotheses may still apply on a second order level. No matter what kind of research you conduct, you can still think of the hypothesis as an educated guess, a prediction of what will happen, an articulation of what you're assuming at the outset of a research project. The hypothesis in this context is roughly synonymous with the argument or claims you're making.

In any context, the researcher is obligated to identify and expose his biases. Let us simply say that in this program, you are qualified to be doing research on homeland security precisely because of those biases and experiences and perspectives, which should be leveraged to your advantage. If you can apply the principles of social scientific inquiry and hold yourself to universal conventions of transparency and rigor, you'll be OK.

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