Week 5: Individual Differences, part 1

- As psychological scientists, we're interested in the fundamental principles of how the mind works. Often, that means thinking about a hypothetical "average" mind, but individual differences can provide additional, unique insights into the mechanisms or principles that we're studying
    - For example, you might find that a treatment works better than some control or placebo. But it invariably works better for some people than others – understanding why that is tells us something about how it works and the condition it's treating
        - Or we might have a problem solving task where people solve the easy problems faster than hard problems. Understanding why some participants find the easy problems *a lot easier* than the hard problems tells us something about the problem solving mechanisms
    - Methods like t-test and ANOVA are all about that central tendency and treat individual differences as noise, which reinforces this idea that we're interested in the behaviour of a hypothetical average individual
        - Multilevel models provide two ways to quantify and analyse individual differences, which will be our topic this week
- The first (and more straight-forward) way is for dealing with individual differences that are "external" to your study. Essentially, these are just additional properties of your participants that you measure in addition to whatever you're studying
        - Here's an example: let's say you're interested in tolerance for deviant behaviour, which you study by asking participants whether it is ok for someone their age to break various rules (cheat on tests, use drugs, steal things, etc.).
        - In addition, you've assessed some other variables: exposure to this kind of deviant behaviour and gender
- You can see here that as kids get older their average tolerance for this kind of behaviour increases, and this seems to be more so for males than for females
- As a starting point, we can ask group-level questions: does tolerance increase with age and is it modulated by gender?
        - In the model we have fixed effects of age, gender, and their interaction
        - And random by-subject intercepts (participants can have different baseline tolerance levels) and slopes (participants can have different rates of increased tolerance)
        - And we've sum-coded gender to get a main effect of age
        - The results shows a significant effect of Age, and no effects of gender
- Now an individual differences question: is this modulated by exposure to deviant behaviour?
        - I don't know the exposure scale here, but the range was about 0.8 to 2, so let's center it to make the other estimates easier to interpret
    - Now we can fit a model that is like the one we had before, but with the addition of this centred exposure variable
- In this model we see significant main effects of age and exposure
        - And significant interactions with exposure: Age-by-Exposure, Gender-by-Exposure, and a three-way interaction of Age-by-Gender-by-Exposure
- I can usually guess what a two-way interaction will look like, and in any case, that's relatively easy to plot and see what it looks like. A three-way interaction is trickier to plot, especially this one, which is a relationship among four variables (Tolerance for deviant behavior, Exposure to deviant behavior, Age, and Gender), and three of those are continuous variables.

        - To make it easier to visualise, we can split exposure into levels as if it were an ordinal variable
    - We can make a median split like this
- Then plot it like this, including both the observed data and the model fits: looks like adolescents with higher Exposure to deviant behaviour tend to have increased Tolerance for deviant behaviour as they get older, and this is stronger for males than for females.
- Median splits are ok, but often I find that a tertile split – so you have a “High”, “Medium”, and “Low” group – provides more information while still being relatively easy to interpret
        - Here’s some code for dividing the exposure variable into three equal groups
- And here’s a plot of that: looks like that interaction is really being driven by the high-exposure males
        - A word of warning: if you use this sort of visualisation strategy, reviewers and readers may get confused about whether your model used continuous or categorical predictors, so you’ll need to be extra clear about this in your write-up.
- That was a little digression into data visualisation and interpreting interactions
        - The key points for this lecture were that individual differences provide deeper insights into group-level phenomena and you can assess them by adding them to the multilevel model

Week 5: Individual Differences, part 2

- The first part of this week's lecture was about "external" individual differences that could just be added as fixed effects to a model. What happens if you're interested in quantifying individual differences that were internal to your study?
- This might happen if you don't have an external measure, or you need to extract individual differences for another analysis (this comes up in my work if I want to assess neural correlates of some individual difference)
    - Random effects provide a way to do this, here's a simple example
    - Imagine you have two participants (A and B) in two conditions (0 and 1). The dashed lines indicate the condition means, those would be the fixed effects
    - The zetas show the individual deviations from those means, those are the random effects
    - Now for participant A, we can we can take the difference between the random effects: that's 1 minus negative 1, which is positive 2
    - For participant B, the same subtraction gives us negative 1 minus 1, which is negative 2
    - So this quite nicely captures the fact that participant A had a larger-than-average effect of condition while participant B had a smaller-than-average effect of condition
    - Notice that, because random effects are deviations from the average, these individual differences are relative to the average effect size, so they'll have positive (larger) and negative (smaller) values even if everyone shows an overall positive (or negative) effect
- That was a very simple example, let's look at how it would work in an actual study. In this simulated data set, we're looking at the effect of a school mental health intervention on educational achievement (math scores)
    - Condition is whether the kids were assigned to receive mental health services or not
    - SDQ is a mental health screening which was given to the treatment group – lower scores are better (less mental health difficulties)
    - Math is their score on a standardised math test
- Here are the data: looks like all kids math scores improved and maybe the treatment group improved faster
    - First, we can ask the group-level question: did the math scores improve more for the treatment group than the control group
    - If there's a group-level effect, then we're going to infer that mental health intervention facilitates academic achievement. If that's true, then the kids who had the most mental health benefit should have the most improvement in math scores -- that's an individual differences question that could provide further support for our inference
- Let's start with the group-level question
    - Like before, we can adjust the time variable to have a sensible intercept
    - Start with a base model that just has an overall effect of time and random by-subject intercepts and slopes
    - Add a baseline effect of treatment condition
    - Then fit the full model with time-by-condition interaction
- When we compare the models, we see there's no significant effect of condition at baseline (the randomisation worked), but there's an effect of slope: the groups started out about the same and the treatment group's math scores improved more rapidly

- The parameter estimates tell basically the same story: no significant effect of condition at baseline and a statistically significant time-by-condition interaction
    - We're taking this to mean that mental health intervention facilitated math learning. As I said, if that's true, then the kids with the most mental health benefit should show the biggest math score improvements
- That's the second question -- individual differences. We can start by just making a plot of individual differences in mental health change. Looks like there was a lot of variability: some people responded really well (big decreases in difficulties on SDQ), some people didn't respond well (increased difficulties according to SDQ).
    - To answer the individual differences question, we want to quantify individual differences in SDQ slopes and math learning slopes, then see if they are related
- Here's the analysis strategy:
    - First, we build separate models of change in SDQ and change in Math scores
    - Then we use the random effects estimated in those models to quantify individual differences in those slopes
    - Then we test the correlation between those individual differences
- Ok, here are the models: pretty simple ones with just the outcome as a function of time, with random by-subject intercepts and slopes. Remember that only the treatment group got the SDQ mental health assessment, so we're fitting these models for just the treatment group's data
- Now we extract the random effects
    - The get_ranef() function is a little helper function I wrote that will extract a random effect from a model and clean it up a bit so it's easier to analyse
    - The merge function combines them into one data frame, aligning the data by ID and giving the math and sdq random effects sensible variable names
    - You can see in the summary there's an ID variable, each participant's random intercepts and slopes for math scores, and random intercepts and slopes for SDQ
- Now we can just see if those random slopes are correlated: indeed they are, $r = -0.77$. That's a strong negative correlation indicating steeper rise in math scores was associated with steeper decrease in mental health difficulties
- Why bother with this random effects business when we could've just fit models for each individual participant and gotten their slopes that way?
    - An individual's performance (on the math test, on the SDQ) is their actual level plus some noise.
    - Individual models (no pooling) don't make that distinction, so you have a noisy estimate of individual differences.
    - Multilevel models reduce the noise component by using the mean and variance of the rest of the group – they *shrink* (or partially pool) the individual estimates toward the group mean based on the distribution of the other individual estimates. This produces a better estimate of true individual differences.
    - See also: Stein's Paradox
- Key points
    - The broad conceptual point from this week is that individual differences provide additional insights into phenomena of interest. You can use them as further tests of a hypothesis
    - When you have a group-level phenomenon or model, you can use the random effects from that model to quantify individual differences
    - Partial pooling / shrinkage improves individual difference estimates