**1. Three Intercepts (Thresholds in Ordinal Logistic Models)**

When you fit an *ordinal* logistic model (often using a cumulative logit link), you get a separate intercept for each “cut‐point” between ordinal categories. For example, if your outcome has 4 ordered categories, you’ll typically see 3 intercepts. Each intercept basically marks the log‐odds boundary that separates category 1 from 2–4, category 1–2 from 3–4, and category 1–3 from 4, and so on.

* **Interpretation:** The *larger* the intercept, the more likely a response is to fall into higher categories. A negative intercept means that, at “baseline” values for all predictors, the probability mass is more on the lower categories.

**2. Estimates for Fixed Effects (Attribute, Rater)**

In an ordinal logistic model, each fixed‐effect estimate tells you how that effect (e.g., a particular lobe or a particular rater) shifts the latent log‐odds of being in higher vs. lower outcome categories.

* **Attribute (lobe) Effects:** A positive coefficient for “LUS” (lung upper segment, say) would mean that compared to your reference category (LLL, etc.), nodules in LUS have higher odds of ending up in higher ordinal categories (whatever your outcome might be).
* **Rater Fixed Effect:** This captures the overall tendency of a particular rater to give higher or lower ratings *across all subjects.* A positive coefficient means that this rater is, on average, more likely to give higher ordinal responses.

**3. Covariance Parameter Estimates (Random Intercepts, Random Rater within Subject)**

When you see something like:

javascript

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Cov Parm Subject Estimate Standard Error

Intercept newID 3.8608 0.5954

rater newID 0.2935 0.1727

it’s telling you:

1. **Random Intercept (Subject‐level)**
   * Each subject (often denoted by newID) gets its own random “shift.” If that random intercept is large, it means there’s a lot of between‐subject variability in overall outcome tendency.
2. **Random Rater by Subject**
   * Here, you’re letting each *subject* have its own random effect for each *rater*. Conceptually, not only do the subjects differ in baseline response, but the difference between Rater JW and Rater VH can *also* vary **across subjects**. In other words, maybe for one subject, JW rates them higher than VH, but for another subject, that difference might vanish or even reverse.

A higher covariance estimate implies more variation among subjects or among subject×rater combinations. A near‐zero covariance would say “subjects don’t differ that much from each other in that dimension.”

**4. Solution for Random Effects**

PROC GLIMMIX (or similar) will often give “predicted” random intercepts or random slopes for each subject (and each rater nested within subject). These are the best linear unbiased predictions (BLUPs).

* **Interpretation of a Random Intercept:** If a particular subject’s random‐intercept estimate is positive, that subject is more prone to end up in higher ordinal categories than the average subject. If negative, they’re more prone to the lower end—given the same fixed effects.
* **Interpretation of a Random Rater** (nested in subject): Tells you how much each subject’s “Rater JW effect,” for example, deviates from the *overall* Rater JW effect. So if the subject×JW random effect is strongly positive, that subject is especially likely to get higher ratings from JW (relative to the average JW–VH difference).

**5. Why Both Fixed and Random Effects for Rater?**

At first glance, it can sound redundant to have “Rater” as both a fixed effect and a random effect. The usual rationale is:

* **Fixed effect:** “On average, across **all** subjects, does Rater JW score differently from VH?” This gives you one overall estimate of that difference and a p‐value for whether it’s different from zero.
* **Random effect (nested in Subject):** “Does the JW–VH difference vary from subject to subject?” If yes, you capture that variability by allowing each subject to have its own random offset for each rater.

In other words, the **fixed** part is the grand mean difference among raters. The **random** part says *some subjects might deviate from that overall difference.* This hierarchical structure is common when you suspect that how raters differ might depend on the specific subject being rated.

*Side note:* If you only have *two* raters total, this approach can be difficult to estimate reliably, but for multiple raters it’s a more standard design.

**Putting It All Together**

So your model says:

1. There are 3 ordinal cut‐points (the intercepts).
2. Different lobes and different raters (on average) shift the log‐odds of the outcome being higher or lower.
3. Each subject has an idiosyncratic random intercept (maybe a “case severity” or “baseline risk” effect).
4. On **top** of that, each subject has its own random *rater* deviations, capturing the idea that Rater JW vs. Rater VH might not be the same difference for all subjects.

Conceptually, that’s what those tables of fixed‐effect estimates, covariance parameters, and random‐effects solutions are telling you.