

Module 6: Random Effects & Linear Mixed Models

A Completely Randomized Design with Random Treatment Effects

Example 6.2: Fast Food Company

A company employs many personnel officers.

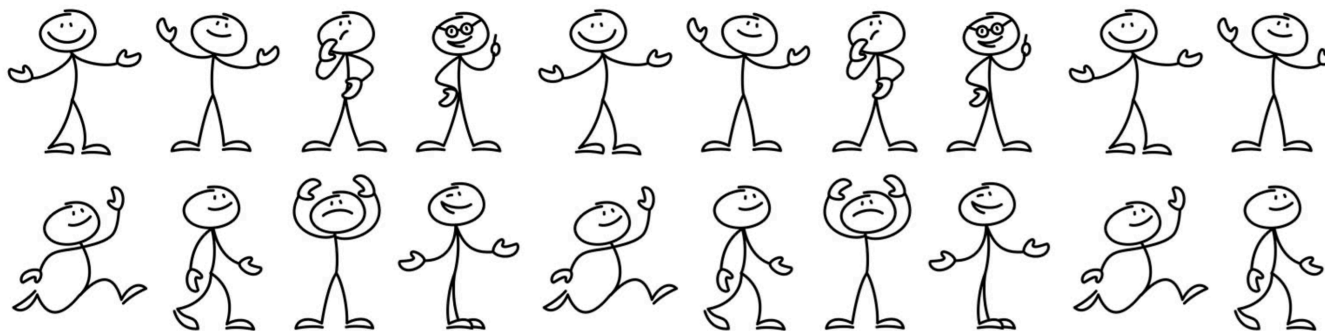
- Five officers were selected at random.
- Each officer rated 4 candidates.

Ratings are from 0–100.

The company wants to know:

- The overall mean rating
- The extent of variability in ratings among officers

Study Blueprint

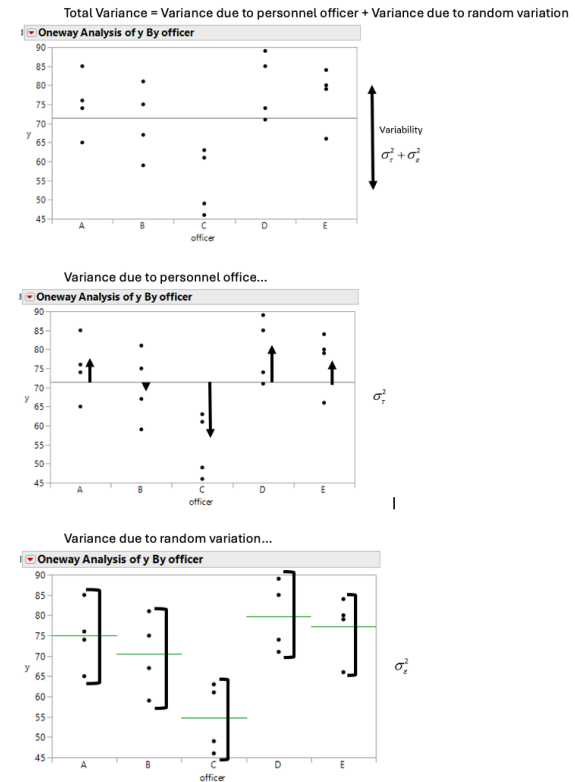


Treatment structure: One-way: Officer (5 levels – officer A, B, C, D, E)

Experimental structure: Officers were randomly assigned to interview $r = 4$ candidates (e.u.) in a CRD. The rating is recorded for each candidate (m.u.).

Officer = Random Treatment Effect

- We are not comparing the mean ratings of officer A vs B vs C.
- We are estimating variability among officers.



The Data

```
1 library(tidyverse)
2 personnel_data <- read_csv("data/06-personnel-data.csv") |>
3   mutate(across(officer:candidate, as.factor))
4 personnel_data
```

```
# A tibble: 20 × 3
  officer candidate rating
  <fct>    <fct>    <dbl>
1 A      1      76
2 A      2      65
3 A      3      85
4 A      4      74
5 B      1      59
6 B      2      75
7 B      3      81
8 B      4      67
9 C      1      49
10 C     2      63
11 C     3      61
12 C     4      46
13 D     1      74
14 D     2      71
15 D     3      85
16 D     4      89
17 E     1      66
18 E     2      84
19 E     3      80
20 E     4      79
```

Statistical Random Effects Model

$$y_{ij} = \mu + t_i + \epsilon_{ij} \text{ for } i = 1, 2, 3, 4, 5; j = 1, 2, 3, 4$$

with:

- $t_i \sim \text{independent } N(0, \sigma_t^2)$
- $\epsilon_{ij} \sim \text{independent } N(0, \sigma_\epsilon^2)$
- t_i is independent ϵ_{ij}

where:

- y_{ij} is the rating of the j^{th} candidate by the i^{th} personnel officer
- μ is the overall grand mean rating
- t_i is the effect of the i^{th} personnel officer who is selected at random
- ϵ_{ij} is the error associated with the j^{th} candidate being rated by the i^{th} personnel officer

REML (Residual Maximum Likelihood) Estimation

Goal: estimate variance components

- σ_t^2 = variability **among officers**
- σ_ϵ^2 = variability **within officer**

Why REML?

- Ordinary ML tends to underestimate variance components (especially with small samples)
- REML adjusts for estimating fixed effects (here, μ) before estimating variances

R: Fitting the Random Effects Model

```
1 library(lme4)
2 personnel_mod <- lmer(rating ~ (1 | officer),
3                       REML = TRUE,
4                       data = personnel_data)
5 summary(personnel_mod)
```

Linear mixed model fit by REML ['lmerMod']
Formula: rating ~ (1 | officer)
Data: personnel_data

REML criterion at convergence: 145.2

Scaled residuals:

	Min	1Q	Median	3Q	Max
	-1.3841	-0.8901	0.2620	0.6496	1.2605

Random effects:

Groups	Name	Variance	Std.Dev.
officer	(Intercept)	80.41	8.967
	Residual	73.28	8.561

Number of obs: 20, groups: officer, 5

Fixed effects:

	Estimate	Std. Error	t value
(Intercept)	71.450	4.444	16.08

Estimating Variances

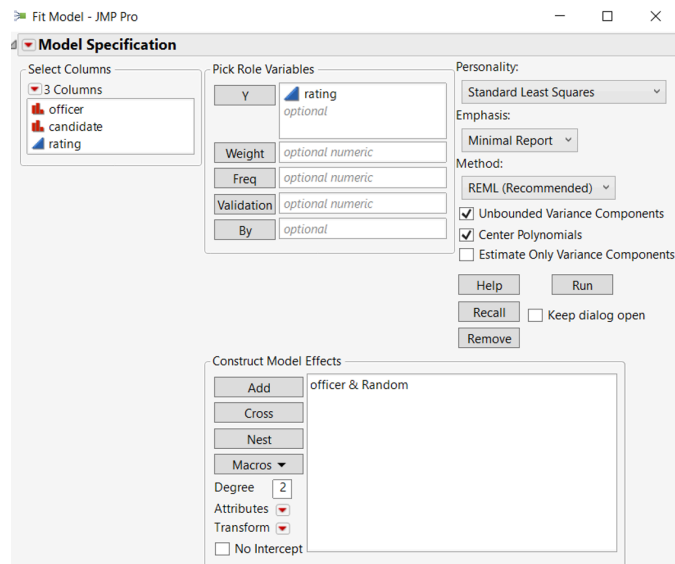
- Total Variance = $\sigma_t^2 + \sigma_\epsilon^2 =$
- What proportion of the total variance is due to personnel officer? $\frac{\sigma_t^2}{\sigma_t^2 + \sigma_\epsilon^2} =$

Estimating the Overall Mean

$\hat{\mu} =$

JMP: Fitting the Random Effects Model

- Analyze > Fit Model
- Highlight officer, then Attributes ♥ > Random Effect
- Set Method: REML



REML Variance Component Estimates							
Random Effect	Var Ratio	Var Component	Std Error	95% Lower	95% Upper	Wald p-Value	Pct of Total
officer	1.0972538	80.410417	70.133327	-57.04838	217.86921	0.2516	52.319
Residual		73.283333	26.75929	39.989606	175.53909		47.681
Total		153.69375	72.64099	72.600381	514.33185		100.000

Parameter Estimates						
Term	Estimate	Std Error	DFDen	t Ratio	Prob> t	
Intercept	71.45	4.443675	4	16.08	<.0001*	