M21 LDT ERP HC ORTHOGRAPIC SENSITIVITY N250

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Set parameters

Set chunk parameters

Load libraries

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Define standard error of the mean function

1 Load and format data files

```
dir_path <- "CSV files"

erp_2 <- read_csv(file.path(dir_path, "m21_ldt_mea_200300_050050_1.csv"))
erp_4 <- read_csv(file.path(dir_path, "m21_ldt_mea_300500_050050_1.csv"))
dmg_lng_vsl <- read_csv(file.path(dir_path, "demo_lang_vsl_pca_hc.csv"))
```

Now we extract `SubjID` from the `ERPset` column

We then join the ERP data and language into a single data frame

Divide into word, non-word and difference wave dataframes

Then we do some more formatting and cleanup of the dataframes.We create separate columns, one for each independent variable (anteriority, laterality, morphological family size). To do this we have to use `seperate` function from the `stringr` package. Run `vignette("programming", package = "dplyr")` to see more about `tidy-selection` and `tidy-evaluation`.

Now we need to extract just the bins and channels that we intend to analyse. For this analysis we will use 9 channels: F3, Fz, F4, C3, Cz, C4, P3, Pz, P4 . We will use the`mutate` function from the `dplyr` package along with the `case_when` function. The `case_when` function is a sequence of two-sided formulas. The left hand side determines which values match this case. The right hand side provides the replacement value.

2 N250 Word Data

2.1 Nested ANOVA Model

```r
#Fit ANOVA model
anova_model_n250_words_b <- mixed(
    value ~ Orthographic_Sensitivity * family_size * base_freq +
    (1 + family_size + base_freq | SubjID) +      # by-subject intercept + slopes
    (1 | SubjID:chlabel),                         # electrode nested within subject
  data   = n250_words_b,
  method = "KR"
)
anova_model_n250_words_b
```

```
|| Mixed Model Anova Table (Type 3 tests, KR-method)
||
|| Model: value ~ Orthographic_Sensitivity * family_size * base_freq +
|| Model:     (1 + family_size + base_freq | SubjID) + (1 | SubjID:chlabel)
|| Data: n250_words_b
||                                            Effect      df         F p.value
|| 1                        Orthographic_Sensitivity   1, 59      0.03    .854
|| 2                                     family_size   1, 59      1.07    .306
|| 3                                       base_freq   1, 59      1.12    .294
|| 4            Orthographic_Sensitivity:family_size   1, 59      0.09    .762
|| 5              Orthographic_Sensitivity:base_freq   1, 59      0.12    .734
|| 6                           family_size:base_freq 1, 1523 35.14 ***   <.001
|| 7 Orthographic_Sensitivity:family_size:base_freq 1, 1523      0.02    .884
|| ---
|| Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '+' 0.1 ' ' 1
```

```r
m1 <- anova_model_n250_words_b$full_model    # Extract the lmer model
ranova(m1) # Run random effects comparison
```

```
|| ANOVA-like table for random-effects: Single term deletions
||
|| Model:
|| value ~ Orthographic_Sensitivity + family_size + base_freq + (1 + family_size + base_freq | SubjID) + (1 | SubjID:chlabel) + Orthographic_Sensi
||                                                         npar  logLik    AIC    LRT Df Pr(>Chisq)
|| <none>                                                    16 -4489.4 9010.8
|| family_size in (1 + family_size + base_freq | SubjID)    13 -4803.0 9631.9 627.07  3  < 2.2e-16 ***
|| base_freq in (1 + family_size + base_freq | SubjID)      13 -4716.5 9459.0 454.13  3  < 2.2e-16 ***
|| (1 | SubjID:chlabel)                                     15 -4684.5 9399.0 390.18  1  < 2.2e-16 ***
|| ---
|| Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
# Extract effect sizes from your ANOVA model
eta_squared(anova_model_n250_words_b, partial = TRUE)
```

```
|| # Effect Size for ANOVA (Type III)
||
|| Parameter                                      | Eta2 (partial) |       95% CI
|| -----------------------------------------------------------------------------
|| Orthographic_Sensitivity                       |       5.82e-04 | [0.00, 1.00]
|| family_size                                    |           0.02 | [0.00, 1.00]
|| base_freq                                      |           0.02 | [0.00, 1.00]
|| Orthographic_Sensitivity:family_size           |       1.56e-03 | [0.00, 1.00]
|| Orthographic_Sensitivity:base_freq             |       1.97e-03 | [0.00, 1.00]
|| family_size:base_freq                          |           0.02 | [0.01, 1.00]
|| Orthographic_Sensitivity:family_size:base_freq |       1.40e-05 | [0.00, 1.00]
||
|| - One-sided CIs: upper bound fixed at [1.00].
```

```r
# Compute Marginal(fixed effects only) and Conditional(fixed + random effects) R²
r2(anova_model_n250_words_b)
```

```
|| # R2 for Mixed Models
||
||   Conditional R2: 0.786
||      Marginal R2: 0.008
```

2.2 Significant Effects

Effect	df	F	p.value	
family_size:base_freq	1, 1523	35.14 ***	<.001	6.76e-03

2.2.1 Main Effects

No significant main effects

2.2.2 Interactions

```
# `base_freq` x `family_size` interaction

# Estimated marginal means for the family_size × base_freq interaction
emm <- emmeans(anova_model_n250_words_b, ~ family_size * base_freq)

# Look at the table of estimated means
emm
```

```
||  family_size  base_freq           emmean    SE   df lower.CL upper.CL
||  Large Family High Base Frequency -0.919 0.284 60.4    -1.49   -0.351
||  Small Family High Base Frequency -0.829 0.352 59.9    -1.53   -0.125
||  Large Family Low Base Frequency  -0.327 0.292 60.3    -0.91    0.256
||  Small Family Low Base Frequency  -0.952 0.344 59.9    -1.64   -0.264
||
|| Results are averaged over the levels of: Orthographic_Sensitivity
|| Degrees-of-freedom method: kenward-roger
|| Confidence level used: 0.95
```

```
# Simple effects of family_size at each level of base_freq
contrast(emm, method = "pairwise", by = "base_freq", adjust = "holm")
```

```
|| base_freq = High Base Frequency:
||  contrast                    estimate    SE   df t.ratio p.value
||  Large Family - Small Family  -0.0895 0.266 65.5  -0.337  0.7375
||
|| base_freq = Low Base Frequency:
||  contrast                    estimate    SE   df t.ratio p.value
||  Large Family - Small Family   0.6246 0.266 65.5   2.350  0.0218
||
|| Results are averaged over the levels of: Orthographic_Sensitivity
|| Degrees-of-freedom method: kenward-roger
```

```
# Simple effects of base_freq at each level of family_size
contrast(emm, method = "pairwise", by = "family_size", adjust = "holm")
```

```
|| family_size = Large Family:
||  contrast                                 estimate   SE df t.ratio p.value
||  High Base Frequency - Low Base Frequency   -0.592 0.23 68  -2.576  0.0122
||
|| family_size = Small Family:
||  contrast                                 estimate   SE df t.ratio p.value
||  High Base Frequency - Low Base Frequency    0.122 0.23 68   0.532  0.5967
||
|| Results are averaged over the levels of: Orthographic_Sensitivity
|| Degrees-of-freedom method: kenward-roger
```

```
# Interaction contrasts (e.g., difference of differences)
contrast(emm, interaction = "pairwise", adjust = "holm")
```

```
||  family_size_pairwise        base_freq_pairwise                       estimate   SE   df t.ratio p.value
||  Large Family - Small Family High Base Frequency - Low Base Frequency   -0.714 0.12 1523  -5.928  <.0001
||
|| Results are averaged over the levels of: Orthographic_Sensitivity
|| Degrees-of-freedom method: kenward-roger
```

For large-family words, N250 amplitude is more negative when base frequency is high than when it is low. For small-family words, base frequency has little effect. For low-frequency bases, small-family words elicit more negative amplitudes than large-family words.

- At **High Base Frequency**: `Large` vs. `Small` family → no difference ($p = .74$). Family size doesn't matter when base frequency is high.
- Within **Small Family**: `High` vs. `Low` base frequency → not significant ($p = .60$). Small-family words are unaffected by base frequency.
- At **Low Base Frequency**: Large vs. Small family → significant difference ($p = .022$). Small-family words yield more negative amplitudes than large-family words, but only when base frequency is low.
- Within **Large Family**: High vs. Low base frequency → significant ($p = .012$). Large-family words show more negative amplitudes when their base frequency is high.

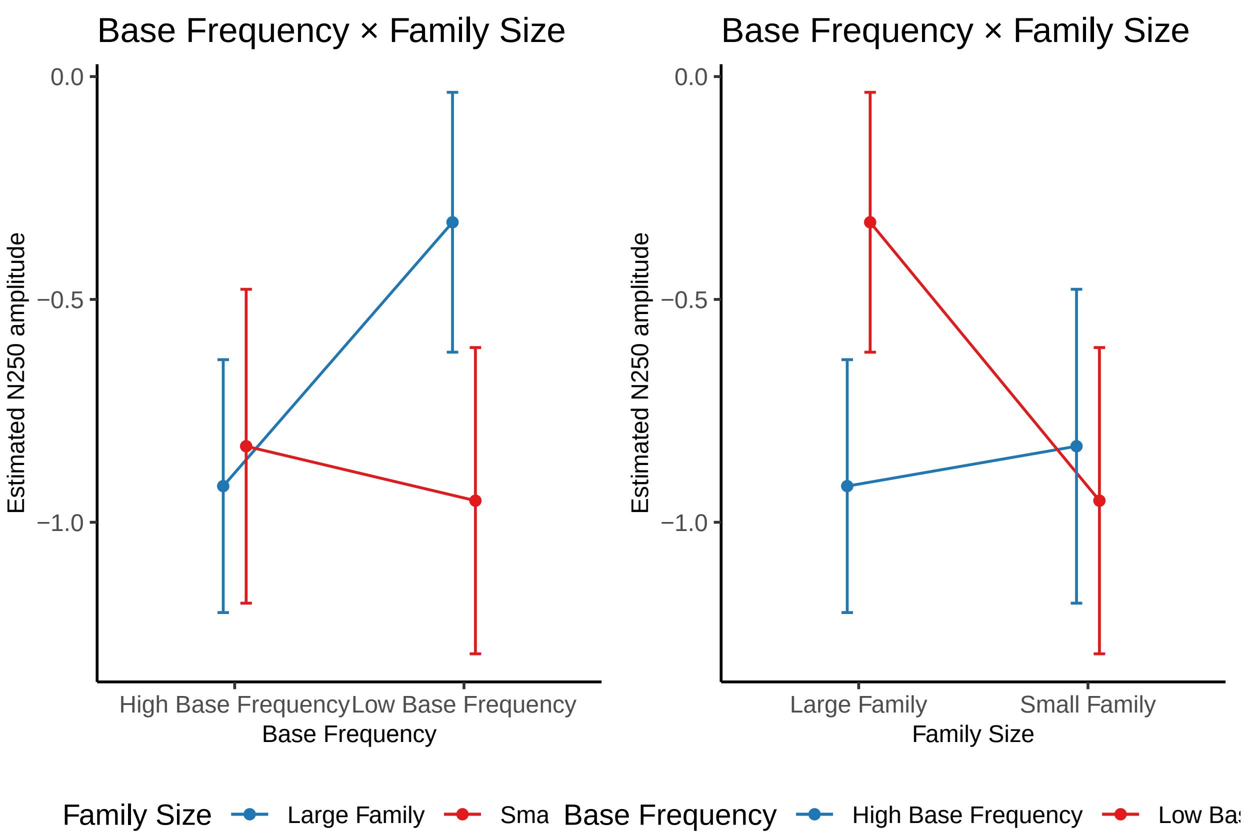
2.3 Plots

```
emm_df <- as.data.frame(emm)
p1<- ggplot(emm_df,
       aes(x = base_freq, y = emmean,
           color = family_size, group = family_size)) +
  geom_line(position = position_dodge(0.2)) +
  geom_point(position = position_dodge(0.2)) +
  geom_errorbar(aes(ymin = emmean - SE, ymax = emmean + SE),
                width = 0.1, position = position_dodge(0.2)) +
```

```
  labs(x = "Base Frequency", y = "Estimated N250 amplitude",
       color = "Family Size",
       title = "Base Frequency × Family Size") +
  scale_color_custom() +
  scale_fill_custom()

p2 <- ggplot(emm_df,
       aes(x = family_size, y = emmean,
           color = base_freq, group = base_freq)) +
  geom_line(position = position_dodge(0.2)) +
  geom_point(position = position_dodge(0.2)) +
  geom_errorbar(aes(ymin = emmean - SE, ymax = emmean + SE),
                width = 0.1, position = position_dodge(0.2)) +
  labs(x = "Family Size", y = "Estimated N250 amplitude",
       color = "Base Frequency",
       title = "Base Frequency × Family Size") +
  scale_color_custom() +
  scale_fill_custom()

plot_grid(p1, p2, ncol = 2)
```



3 N250 Nonword Data

3.1 Compute the ANOVA

```
anova_model_n250_nonwords <- mixed(
    value ~ Orthographic_Sensitivity * family_size * complexity +
    (1 + family_size + complexity | SubjID) +      # by-subject intercept + slopes
    (1 | SubjID:chlabel),                         # electrode nested within subject
  data   = n250_nonwords,
  method = "KR"
)
anova_model_n250_nonwords
```

```
|| Mixed Model Anova Table (Type 3 tests, KR-method)
||
|| Model: value ~ Orthographic_Sensitivity * family_size * complexity +
|| Model:     (1 + family_size + complexity | SubjID) + (1 | SubjID:chlabel)
|| Data: n250_nonwords
||                                            Effect      df      F p.value
|| 1                        Orthographic_Sensitivity   1, 59   0.05    .823
|| 2                                     family_size   1, 59   0.11    .738
|| 3                                      complexity   1, 59   0.01    .926
|| 4            Orthographic_Sensitivity:family_size   1, 59   0.00    .989
|| 5             Orthographic_Sensitivity:complexity   1, 59   0.20    .653
|| 6                          family_size:complexity 1, 1523   1.92    .166
|| 7 Orthographic_Sensitivity:family_size:complexity 1, 1523 4.58 *    .033
|| ---
|| Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '+' 0.1 ' ' 1
```

```
m1 <- anova_model_n250_nonwords$full_model    # Extract the lmer model
ranova(m1)    # Run random effects comparison
```

```
|| ANOVA-like table for random-effects: Single term deletions
||
|| Model:
|| value ~ Orthographic_Sensitivity + family_size + complexity + (1 + family_size + complexity | SubjID) + (1 | SubjID:chlabel) + Orthographic_Sen
||                                                           npar  logLik    AIC    LRT Df Pr(>Chisq)
|| <none>                                                      16 -4507.1 9046.2
|| family_size in (1 + family_size + complexity | SubjID)   13 -4722.5 9471.1 430.90  3  < 2.2e-16 ***
|| complexity in (1 + family_size + complexity | SubjID)    13 -4855.6 9737.3 697.12  3  < 2.2e-16 ***
|| (1 | SubjID:chlabel)                                      15 -4708.3 9446.5 402.33  1  < 2.2e-16 ***
|| ---
|| Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
# Extract effect sizes from your ANOVA model
eta_squared(anova_model_n250_nonwords, partial = TRUE)
```

```
|| # Effect Size for ANOVA (Type III)
||
|| Parameter                                       | Eta2 (partial) |       95% CI
|| --------------------------------------------------------------------------------
|| Orthographic_Sensitivity                        |       8.51e-04 | [0.00, 1.00]
|| family_size                                     |       1.90e-03 | [0.00, 1.00]
|| complexity                                      |       1.48e-04 | [0.00, 1.00]
|| Orthographic_Sensitivity:family_size            |       2.97e-06 | [0.00, 1.00]
|| Orthographic_Sensitivity:complexity             |       3.44e-03 | [0.00, 1.00]
|| family_size:complexity                          |       1.26e-03 | [0.00, 1.00]
|| Orthographic_Sensitivity:family_size:complexity |       3.00e-03 | [0.00, 1.00]
||
|| - One-sided CIs: upper bound fixed at [1.00].
```

```
# Compute Marginal(fixed effects only) and Conditional(fixed + random effects) R²
r2(anova_model_n250_nonwords)
```

```
|| # R2 for Mixed Models
||
||   Conditional R2: 0.759
||      Marginal R2: 0.002
```

3.2 Main Effects

No main effects.

3.3 Interactions

A three way interaction between

- `Sensitivity × Family Size × Complexity`: significant (p =.033).

3.3.1 Simple Contrasts

Compare High vs Low Orthographic Sensitivity within each combination of Family Size and Complexity

This gives you: 4 contrasts: one for each `Family Size × Complexity` combination. Each shows whether `High` vs `Low Orthographic Sensitivity` differs significantly

If simple effects aren't significant, try looking at interaction contrasts, which test differences in the differences. You're now asking: Does the effect of Sensitivity change more in some complexity/family combinations than others?

```r
# 1. Get the EMM grid for all combinations
(emm1 <- emmeans(anova_model_n250_nonwords, ~ Orthographic_Sensitivity * family_size * complexity))
```

```
||  Orthographic_Sensitivity family_size  complexity emmean    SE   df lower.CL upper.CL
||  High Orthographic        Large Family Complex    -0.495 0.400 60.2    -1.29   0.3048
||  Low Orthographic         Large Family Complex    -0.607 0.449 60.2    -1.50   0.2899
||  High Orthographic        Small Family Complex    -0.785 0.377 60.4    -1.54  -0.0312
||  Low Orthographic         Small Family Complex    -0.632 0.423 60.4    -1.48   0.2138
||  High Orthographic        Large Family Simple     -0.609 0.398 60.2    -1.40   0.1858
||  Low Orthographic         Large Family Simple     -0.713 0.446 60.2    -1.61   0.1799
||  High Orthographic        Small Family Simple     -0.471 0.393 60.3    -1.26   0.3151
||  Low Orthographic         Small Family Simple     -0.829 0.441 60.3    -1.71   0.0542
||
|| Degrees-of-freedom method: kenward-roger
|| Confidence level used: 0.95
```

```r
# "Simple effects" contrasts:
#    a) Effect of complexity within each Sensitivity × family_size cell
(contrast(emm1, method = "pairwise", by = c("Orthographic_Sensitivity", "family_size"),
         simple = "complexity", adjust = "holm"))
```

```
|| Orthographic_Sensitivity = High Orthographic, family_size = Large Family:
||  contrast         estimate    SE   df t.ratio p.value
||  Complex - Simple    0.115 0.377 64.8   0.304  0.7619
||
|| Orthographic_Sensitivity = Low Orthographic, family_size = Large Family:
||  contrast         estimate    SE   df t.ratio p.value
||  Complex - Simple    0.105 0.424 64.8   0.249  0.8045
||
|| Orthographic_Sensitivity = High Orthographic, family_size = Small Family:
||  contrast         estimate    SE   df t.ratio p.value
||  Complex - Simple   -0.313 0.377 64.8  -0.830  0.4094
||
|| Orthographic_Sensitivity = Low Orthographic, family_size = Small Family:
||  contrast         estimate    SE   df t.ratio p.value
||  Complex - Simple    0.197 0.424 64.8   0.464  0.6440
||
|| Degrees-of-freedom method: kenward-roger
```

```r
#    b) Effect of family_size within each Sensitivity × complexity cell
(contrast(emm1, method = "pairwise", by = c("Orthographic_Sensitivity", "complexity"),
         simple = "family_size", adjust = "holm"))
```

```
|| Orthographic_Sensitivity = High Orthographic, complexity = Complex:
||  contrast                    estimate    SE   df t.ratio p.value
||  Large Family - Small Family   0.2902 0.301 68.5   0.963  0.3388
||
|| Orthographic_Sensitivity = Low Orthographic, complexity = Complex:
||  contrast                    estimate    SE   df t.ratio p.value
||  Large Family - Small Family   0.0246 0.338 68.5   0.073  0.9422
||
|| Orthographic_Sensitivity = High Orthographic, complexity = Simple:
||  contrast                    estimate    SE   df t.ratio p.value
||  Large Family - Small Family  -0.1380 0.301 68.5  -0.458  0.6482
||
|| Orthographic_Sensitivity = Low Orthographic, complexity = Simple:
||  contrast                    estimate    SE   df t.ratio p.value
||  Large Family - Small Family   0.1160 0.338 68.5   0.343  0.7326
||
|| Degrees-of-freedom method: kenward-roger
```

```r
#    c) Effect of Sensitivity within each family_size × complexity cell
(contrast(emm1, method = "pairwise", by = c("family_size", "complexity"),
         simple = "Orthographic_Sensitivity", adjust = "holm"))
```

```
|| family_size = Large Family, complexity = Complex:
||  contrast                            estimate    SE   df t.ratio p.value
||  High Orthographic - Low Orthographic    0.113 0.601 60.2   0.187  0.8520
||
|| family_size = Small Family, complexity = Complex:
||  contrast                            estimate    SE   df t.ratio p.value
||  High Orthographic - Low Orthographic   -0.153 0.566 60.4  -0.270  0.7880
||
```

```
|| family_size = Large Family, complexity = Simple:
||  contrast                             estimate    SE   df t.ratio p.value
||  High Orthographic - Low Orthographic    0.103 0.598 60.2   0.172  0.8637
||
|| family_size = Small Family, complexity = Simple:
||  contrast                             estimate    SE   df t.ratio p.value
||  High Orthographic - Low Orthographic    0.357 0.591 60.3   0.604  0.5481
||
|| Degrees-of-freedom method: kenward-roger
```

3.3.2 Interaction Contrasts

The interaction contrast tests:

Is the difference in the effect of A across levels of B different at Complex vs. Simple levels?

Mathematically

You're testing:

$$[[(A_1 - A_2) \text{ in } B_1] - [(A_1 - A_2) \text{ in } B_2] \text{ in Condition } C_1] - [[(A_1 - A_2) in B_1] - [(A_1 - A_2) in B_2] \text{in Condition } C_2]$$

```r
#  Interaction contrasts (difference-of-differences)
#    Compare (complexity effect in large vs small family) across sensitivity
(contrast(emm1, interaction = c("pairwise", "pairwise"), by = NULL, adjust = "holm"))
```

```
||  Orthographic_Sensitivity_pairwise    family_size_pairwise        complexity_pairwise estimate    SE   df t.ratio p.value
||  High Orthographic - Low Orthographic Large Family - Small Family Complex - Simple        0.52 0.243 1523   2.140  0.0325
||
|| Degrees-of-freedom method: kenward-roger
```

```r
# (contrast(emm1, interaction = c("pairwise", "pairwise"), combine = TRUE, adjust = "bonferroni"))

# Optionally: get confidence intervals
(confint(contrast(emm1, interaction = c("pairwise", "pairwise"))))
```

```
||  Orthographic_Sensitivity_pairwise    family_size_pairwise        complexity_pairwise estimate    SE   df lower.CL upper.CL
||  High Orthographic - Low Orthographic Large Family - Small Family Complex - Simple        0.52 0.243 1523   0.0433    0.996
||
|| Degrees-of-freedom method: kenward-roger
|| Confidence level used: 0.95
```

```r
all_contr <- contrast(emm1, interaction = c("pairwise", "pairwise"), combine = TRUE, adjust = "bonferroni")

# 1. Summarize contrasts
sumc <- summary(all_contr)

# Construct a contrast name string
contrast_name <- paste( sumc$Orthographic_Sensitivity_pairwise, sumc$family_size_pairwise,
  sumc$complexity_pairwise,sep = " - ")  # or whatever separator you prefer

# 2. Extract values
est <- sumc$estimate
se <- sumc$SE
df_contr <- sumc$df

# 3. Use the sigma you found
lm_mod <- anova_model_n250_nonwords$full_model
sigma_val <- sigma(lm_mod)

# 4. Compute d and its SE
d <- est / sigma_val
se_d <- se / sigma_val

# 5. Confidence intervals for d (t critical)
alpha <- 0.05
tcrit <- qt(1 - alpha/2, df_contr)
ci_low <- d - tcrit * se_d
ci_high <- d + tcrit * se_d

# 6. Make table
d_table <- data.frame( contrast = contrast_name,
                       d = d, se_d = se_d, df = df_contr, ci_low = ci_low, ci_high = ci_high)
d_table
```

```
||                                                                                   contrast         d      se_d   df     ci_low   ci_high
|| 1 High Orthographic - Low Orthographic - Large Family - Small Family - Complex - Simple 0.3677209 0.1718511 1523 0.03063102 0.7048107
```

Compute the effect of Complexity (Complex - Simple) within each Orthographic Sensitivity × Family Size combination. High Sensitivity-Large Family: `Complex - Simple = -0.495 - (-0.609) = +0.114`

High Sensitivity- Small Family: `Complex - Simple = -0.785 - (-0.471) = -0.314`

Low Sensitivity - Large Family: `Complex - Simple = -0.607 - (-0.713) = +0.106`

Low Sensitivity - Small Family: `Complex - Simple = -0.632 - (-0.829) = +0.197`

Compute the difference of differences: compare how the effect of complexity differs across sensitivity groups: `(High Sensitivity complexity effect) - (Low Sensitivity complexity effect)`

For Large Family:

```
High:  +0.114
Low:   +0.106
Difference: 0.114 - 0.106 = +0.008
```

For Small Family:

```
High: -0.314
Low:  +0.197
Difference: -0.314 - (+0.197) = -0.511
```

This is a reversal of the complexity effect between High and Low sensitivity participants for Small Family nonwords — and that's the core of your significant 3-way interaction.

Now take the difference of these differences (Small - Large): `-0.511 - 0.008 = -0.519`. That's the interaction contrast estimate: `-0.52, p = .0325`

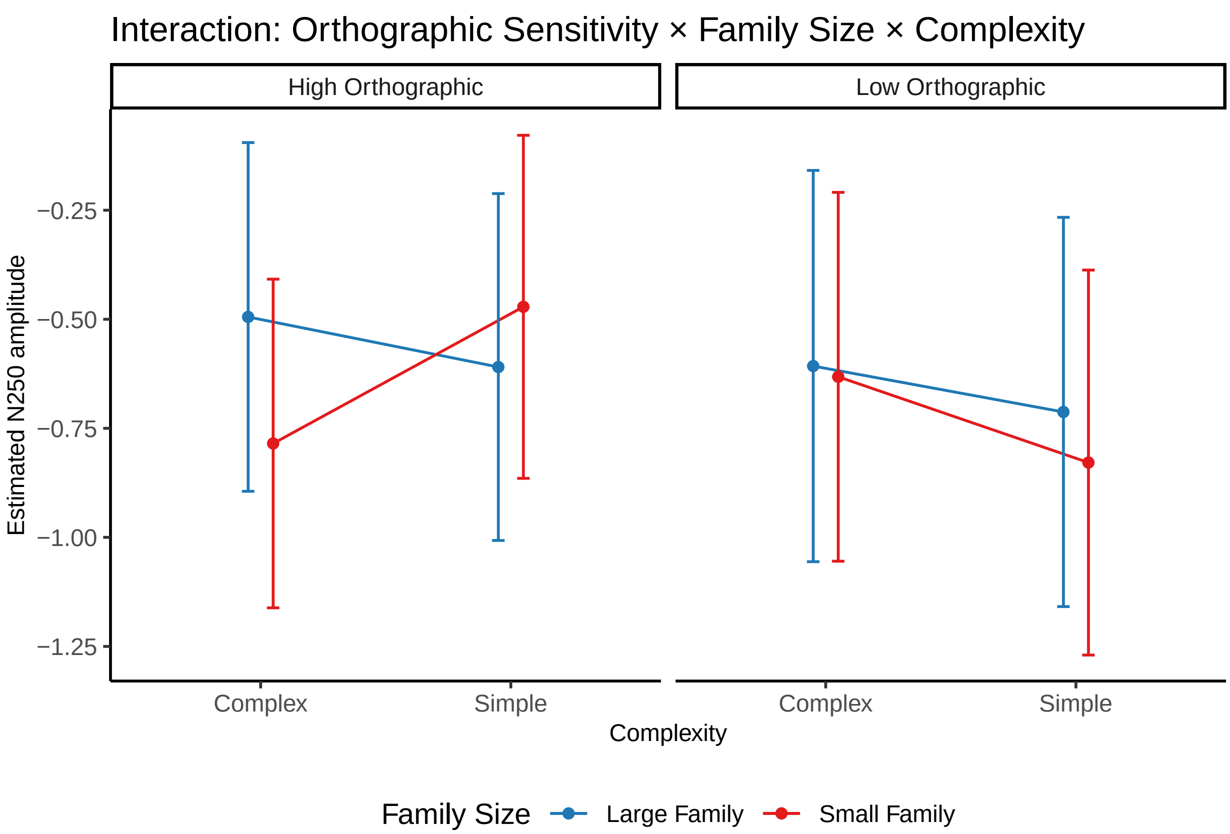
The three-way interaction reflects the fact that High and Low sensitivity participants show opposite complexity effects — but only in the Small Family condition. In Large families, their complexity effects are essentially the same.

In `Small families`, `High sensitivity` participants respond more negatively to `complex items`, white `Low sensitivity` participants respond more negatively to `simple items`.

This crossover in the complexity effect is what drives the significant interaction — even though none of the simple effects are individually significant.

```
# 6. Plot the interaction
library(ggplot2)

emm1_df <- as.data.frame(emm1)
ggplot(emm1_df,
       aes(x = complexity, y = emmean,
           color = family_size, group = family_size)) +
  facet_wrap(~ Orthographic_Sensitivity) +
  geom_line(position = position_dodge(0.2)) +
  geom_point(position = position_dodge(0.2)) +
  geom_errorbar(aes(ymin = emmean - SE, ymax = emmean + SE),
                width = 0.1, position = position_dodge(0.2)) +
  labs(x = "Complexity", y = "Estimated N250 amplitude",
       color = "Family Size",
       title = "Interaction: Orthographic Sensitivity × Family Size × Complexity") +
  scale_color_custom() +
  scale_fill_custom()
```



Interpretation - This is an interaction contrast (a "contrast of contrasts") across your three factors (Orthographic Sensitivity × Family Size × Complexity).

- Specifically, it is testing whether the difference (`Complex - Simple`) for (`Large Family` vs. `Small Family`) differs between the two levels of `Orthographic Sensitivity`.

The contrast is asking: "Is the effect of `complexity`, in the contrast `Large` vs. `Small` family, different in `High Orthographic` vs.`Low Orthographic` participants?"

- The `estimate = 0.52` is the difference in differences (i.e. the slope difference) on your response metric (N250 amplitude).
  - $SE = 0.243$, $df = 1523$, $t = 2.140 \rightarrow$ yields $p = 0.0325$, so it is statistically significant (given Bonferroni correction, etc.).
- Because you used adjust = "bonferroni" and combine = TRUE, this contrast is part of a "family" of interaction contrasts that have been adjusted for multiple comparisons.

So in more conversational terms: you have evidence that High Orthographic readers show a different `complexity × family size` effect than Low Orthographic readers — in particular, in how the `complexity` effect (`Complex` vs. `Simple`) differs when comparing `Large` vs. `Small` family.

Suggests that sensitivity does influence the N250, but only in how it modulates the joint effect of family size and complexity. In other words: the way family size and complexity interact depends on whether participants are orthographically sensitive or not.

- Marginal $R^2 = 0.2$ –> the fixed predictors (including sensitivity) account for very little variance overall.
- Conditional $R^2 = 76$ –> most variance is indeed explained by subjects and electrodes (as anticipated).

Most of the variability in N250 amplitude reflects differences across participants and electrode sites, as expected for ERP data. Orthographic sensitivity did not produce an overall shift in N250 responses, but it did moderate the combined influence of family size and morphological complexity. This interaction was statistically significant but accounted for only a very small portion of the variance. Thus, orthographic sensitivity may play a role in how multiple lexical factors are integrated during early morphological processing, though the effect is subtle.