M21 LDT ERP HC ORTHOGRAPIC SENSITIVITY N250 Family Size

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Contents

Set parameters

Set chunk parameters

Load libraries

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Define standard error of the mean function

1 Load data files

```
dir_path <- "CSV files"

erp_2A <- read_csv(file.path(dir_path, "fs_m21_ldt_mea_200300_050050_1_AB.csv"))
erp_2B <- read_csv(file.path(dir_path, "fs_m21_ldt_mea_200300_050050_1_BA.csv"))

dmg_lng_vsl <- read_csv(file.path(dir_path, "demo_lang_vsl_pca_hc.csv"))
```

```
library(dplyr)

erp_2i <- bind_rows(
  erp_2A |> mutate(List = "AB"),
  erp_2B |> mutate(List = "BA")
)
```

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

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

2 Format data files

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.

3 N250 Word Data

Statistical analysis.

Linear mixed-effects models were fit using the afex::mixed function (method = "KR") to account for both subject-level and electrode-level variability. Each model included random intercepts for participants (SubjID) and electrodes nested within participants (SubjID:chlabel), as well as by-subject random slopes for within-subject factors (Family Size, Complexity, or Base Frequency, depending on the analysis). When a significant interaction was obtained, we probed it using estimated marginal means from the fitted model (emmeans package) to clarify the source of the effect. Because these follow-up contrasts were intended to interpret a significant higher-order interaction rather than to test independent hypotheses, we reported uncorrected p-values (adjust = "none") for interpretive clarity. The robustness of the overall pattern was verified using a Holm correction, which did not change the substantive conclusions.

3.1 Nested ANOVA Model

```
n250_words_b %>%
  count(family_size, base_freq, Orthographic_Sensitivity)
```

```
|| # A tibble: 8 x 4
||   family_size base_freq Orthographic_Sensitivity     n
||   <chr>       <chr>     <chr>                    <int>
|| 1 Large       High      High Orthographic          306
|| 2 Large       High      Low Orthographic           234
|| 3 Large       Low       High Orthographic          306
|| 4 Large       Low       Low Orthographic           234
|| 5 Small       High      High Orthographic          306
|| 6 Small       High      Low Orthographic           234
|| 7 Small       Low       High Orthographic          306
|| 8 Small       Low       Low Orthographic           234
```

```
#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, 58      0.02    .889
|| 2                                       family_size   1, 58      1.38    .246
|| 3                                         base_freq   1, 58      0.55    .463
|| 4              Orthographic_Sensitivity:family_size   1, 58      0.01    .912
|| 5                Orthographic_Sensitivity:base_freq   1, 58      0.00    .981
|| 6                             family_size:base_freq 1, 1498 33.27 ***   <.001
|| 7 Orthographic_Sensitivity:family_size:base_freq 1, 1498      0.00    .954
|| ---
|| Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '+' 0.1 ' ' 1
```

```
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 -4429.3 8890.5
|| family_size in (1 + family_size + base_freq | SubjID)   13 -4738.9 9503.9 619.36  3  < 2.2e-16 ***
|| base_freq in (1 + family_size + base_freq | SubjID)     13 -4646.0 9318.0 433.50  3  < 2.2e-16 ***
|| (1 | SubjID:chlabel)                                 15 -4622.9 9275.7 387.19  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                     |       3.39e-04 | [0.00, 1.00]
|| family_size                                  |           0.02 | [0.00, 1.00]
|| base_freq                                    |       9.33e-03 | [0.00, 1.00]
|| Orthographic_Sensitivity:family_size         |       2.11e-04 | [0.00, 1.00]
|| Orthographic_Sensitivity:base_freq           |       9.55e-06 | [0.00, 1.00]
|| family_size:base_freq                        |           0.02 | [0.01, 1.00]
|| Orthographic_Sensitivity:family_size:base_freq |     2.26e-06 | [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: 0.788
||      Marginal R2: 0.007
```

3.2 Main Effects

No significant main effects

3.3 Interactions

Effect	df	F	p.value	
family__size:base__freq	1, 1498	33.27 ***	<.001	0.02

3.3.1 Simple Contrasts

```r
# Estimated marginal means for the family_size × base frequency interaction
(emm1 <- emmeans(anova_model_n250_words_b, ~ family_size * base_freq))
```

```
||  family_size base_freq emmean    SE   df lower.CL upper.CL
||  Large       High      -0.862 0.286 59.4   -1.434  -0.2897
||  Small       High      -0.818 0.360 58.9   -1.539  -0.0969
||  Large       Low       -0.345 0.299 59.2   -0.943   0.2536
||  Small       Low       -1.007 0.354 58.9   -1.715  -0.2986
||
|| Results are averaged over the levels of: Orthographic_Sensitivity
|| Degrees-of-freedom method: kenward-roger
|| Confidence level used: 0.95
```

```r
# Get all pairwise contrasts
emm1_contrasts <- contrast(emm1,  method = "pairwise", by = NULL, adjust = "none")
emm1_contrasts
```

```
||  contrast                estimate    SE   df t.ratio p.value
||  Large High - Small High  -0.0439 0.271 64.4  -0.162  0.8716
||  Large High - Large Low   -0.5174 0.231 67.1  -2.244  0.0281
||  Large High - Small Low    0.1450 0.327 58.0   0.444  0.6589
||  Small High - Large Low   -0.4735 0.362 58.0  -1.308  0.1961
||  Small High - Small Low    0.1889 0.231 67.1   0.819  0.4154
||  Large Low - Small Low     0.6624 0.271 64.4   2.447  0.0171
||
|| Results are averaged over the levels of: Orthographic_Sensitivity
|| Degrees-of-freedom method: kenward-roger
```

```r
# Keep only the contrasts you want
# Simple effects of family_size at each level of base_freq
# Simple effects of base_freq at each level of family_size
keep <- c("Large High - Small High",
          "Large Low - Small Low",
```

```r
         "Large High - Large Low",
         "Small High - Small Low")
(emm1_contrasts_filtered <- subset(emm1_contrasts, contrast %in% keep))
```

```
||  contrast                estimate    SE   df t.ratio p.value
||  Large High - Small High  -0.0439 0.271 64.4  -0.162  0.8716
||  Large High - Large Low   -0.5174 0.231 67.1  -2.244  0.0281
||  Small High - Small Low    0.1889 0.231 67.1   0.819  0.4154
||  Large Low - Small Low     0.6624 0.271 64.4   2.447  0.0171
||
|| Results are averaged over the levels of: Orthographic_Sensitivity
|| Degrees-of-freedom method: kenward-roger
```

```r
# Get Confidence Intervals
(emm1_contrasts_filtered_ci <- confint(emm1_contrasts_filtered))
```

```
||  contrast                estimate    SE   df lower.CL upper.CL
||  Large High - Small High  -0.0439 0.271 64.4   -0.585   0.4968
||  Large High - Large Low   -0.5174 0.231 67.1   -0.978  -0.0573
||  Small High - Small Low    0.1889 0.231 67.1   -0.271   0.6491
||  Large Low - Small Low     0.6624 0.271 64.4    0.122   1.2031
||
|| Results are averaged over the levels of: Orthographic_Sensitivity
|| Degrees-of-freedom method: kenward-roger
|| Confidence level used: 0.95
```

```r
# Get effect sizes
# Get all pairwise effect sizes
effs1 <- eff_size(emm1, sigma = sigma(m1), edf = df.residual(m1))

# Remove the two redundant rows (rows 3 and 4)
(effs1_filtered <- subset(effs1, !contrast %in% c("Large Family High Base Frequency - Small Family Low Base Frequency",
                                                   "Small Family High Base Frequency - Large Family Low Base Frequency")))
```

```
||  contrast                effect.size    SE   df lower.CL upper.CL
||  Large High - Small High     -0.0312 0.192 58.9  -0.4153   0.3530
||  Large High - Large Low      -0.3669 0.164 59.2  -0.6942  -0.0396
||  Large High - Small Low       0.1028 0.232 58.9  -0.3609   0.5666
||  Small High - Large Low      -0.3358 0.257 58.9  -0.8496   0.1781
||  Small High - Small Low       0.1340 0.164 58.9  -0.1932   0.4612
||  Large Low - Small Low        0.4697 0.192 58.9   0.0853   0.8541
||
|| Results are averaged over the levels of: Orthographic_Sensitivity
|| sigma used for effect sizes: 1.41
|| Degrees-of-freedom method: inherited from kenward-roger when re-gridding
|| Confidence level used: 0.95
```

For large-family words, N250 amplitude is more negative when base frequency is high (-0.86) than when it is low (-0.35). For small-family words, base frequency has little effect (-0.82 for high vs -1.01 for low). For low-frequency bases, small-family words elicit more negative amplitudes (-1.01) than large-family words (-0.35). For high-frequency bases, family size has little effect (-0.86 for large vs -0.82 for small).

3.3.2 Interaction Contrasts

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

```
||  family_size_pairwise base_freq_pairwise estimate    SE   df t.ratio p.value
||  Large - Small        High - Low           -0.706 0.122 1498  -5.768  <.0001
||
|| Results are averaged over the levels of: Orthographic_Sensitivity
|| Degrees-of-freedom method: kenward-roger
```

```r
confint(contrast(emm1, interaction = c("pairwise", "pairwise")))
```

```
||  family_size_pairwise base_freq_pairwise estimate    SE   df lower.CL upper.CL
||  Large - Small        High - Low           -0.706 0.122 1498   -0.947   -0.466
||
|| Results are averaged over the levels of: Orthographic_Sensitivity
|| Degrees-of-freedom method: kenward-roger
|| Confidence level used: 0.95
```

```r
# Get confidence intervals, for each base frequency effect for each family size and then for interaction effect
confint(contrast(emmeans(m1, ~ family_size | base_freq), "pairwise"))
```

```
|| base_freq = High:
||  contrast      estimate    SE   df lower.CL upper.CL
||  Large - Small  -0.0439 0.271 64.4   -0.585    0.497
||
|| base_freq = Low:
```

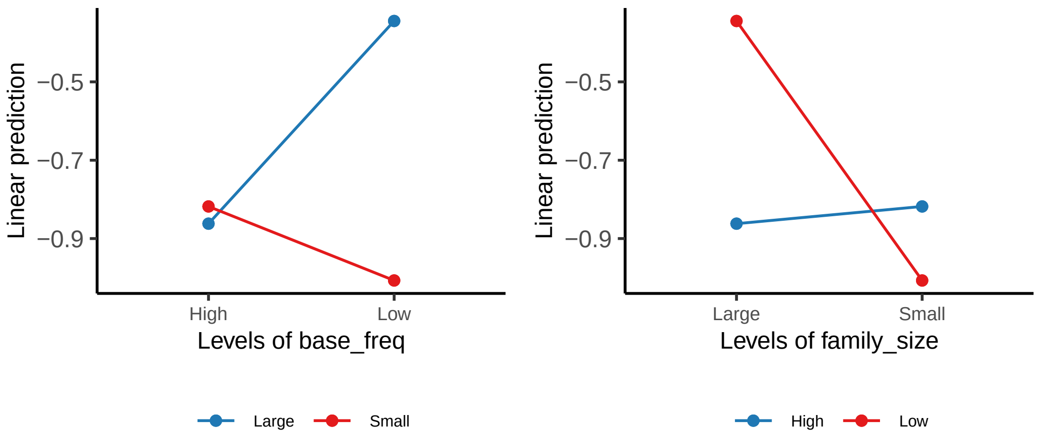
```
||  contrast      estimate    SE   df lower.CL upper.CL
||  Large - Small   0.6624 0.271 64.4    0.122    1.203
||
|| Results are averaged over the levels of: Orthographic_Sensitivity
|| Degrees-of-freedom method: kenward-roger
|| Confidence level used: 0.95
```

There is a robust crossover interaction: the base-frequency effect is significant in opposite directions for large vs. small family words.

3.4 Plots

```
p1 <- emmip(anova_model_n250_words_b, family_size ~ base_freq) + my_style
p2 <- emmip(anova_model_n250_words_b, base_freq ~  family_size) + my_style

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



4 N250 Nonword Data

```
n250_nonwords %>%
  count(family_size, complexity, Orthographic_Sensitivity)
```

4.1 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, 58   0.12    .725
|| 2                                    family_size   1, 58   0.52    .476
|| 3                                     complexity   1, 58   2.43    .124
|| 4           Orthographic_Sensitivity:family_size   1, 58   0.17    .683
|| 5            Orthographic_Sensitivity:complexity   1, 58 3.13 +    .082
|| 6                         family_size:complexity 1, 1498   0.11    .744
|| 7 Orthographic_Sensitivity:family_size:complexity 1, 1498 3.27 +    .071
|| ---
|| Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '+' 0.1 ' ' 1
```

```
m2 <- anova_model_n250_nonwords$full_model    # Extract the lmer model
ranova(m2)    # 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 -4427.7 8887.4
|| family_size in (1 + family_size + complexity | SubjID)   13 -4616.2 9258.4 377.09  3  < 2.2e-16 ***
|| complexity in (1 + family_size + complexity | SubjID)    13 -4727.3 9480.7 599.34  3  < 2.2e-16 ***
|| (1 | SubjID:chlabel)                                    15 -4630.3 9290.5 405.15  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                        |       2.15e-03 | [0.00, 1.00]
|| family_size                                     |       8.81e-03 | [0.00, 1.00]
|| complexity                                      |           0.04 | [0.00, 1.00]
|| Orthographic_Sensitivity:family_size            |       2.90e-03 | [0.00, 1.00]
|| Orthographic_Sensitivity:complexity             |           0.05 | [0.00, 1.00]
|| family_size:complexity                          |       7.14e-05 | [0.00, 1.00]
|| Orthographic_Sensitivity:family_size:complexity |       2.18e-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: 0.756
||      Marginal R2: 0.012
```

4.2 Main Effects and Interactions

No main effects emerged, but there are two marginal effects suggesting a subtle modulation by orthographic sensitivity:

- A trend for `Orthographic_Sensitivity × Complexity`, $F(1, 58) = 3.13$, $p = .082$
- A trend for `Orthographic_Sensitivity × Family_Size × Complexity`, $F(1, 1498) = 3.27$, $p = .071$

These trends imply that the complexity effect (and perhaps its relation to family size) may differ between participants high vs. low in orthographic sensitivity.

```r
# Estimated marginal means for the Orthographic_Sensitivity * complexity interaction
(emm2 <- emmeans(anova_model_n250_nonwords, ~ Orthographic_Sensitivity  * complexity))
```

```
||  Orthographic_Sensitivity complexity emmean    SE df lower.CL upper.CL
||  High Orthographic        Simple     -0.555 0.329 58    -1.21    0.104
||  Low Orthographic         Simple     -1.184 0.376 58    -1.94   -0.430
||  High Orthographic        Complex    -0.610 0.381 58    -1.37    0.153
||  Low Orthographic         Complex    -0.317 0.436 58    -1.19    0.555
||
|| Results are averaged over the levels of: family_size
|| Degrees-of-freedom method: kenward-roger
|| Confidence level used: 0.95
```

```r
# Get all pairwise contrasts
emm2_contrasts <- contrast(emm2,  method = "pairwise", by = NULL, adjust = "none")
# emm2_contrasts

# Keep only the contrasts you want
# Simple effects of family_size at each level of complexity
# Simple effects of complexity at each level of family_size
keep2 <- c("High Orthographic Complex - High Orthographic Simple",
           "Low Orthographic Complex - Low Orthographic Simple",
           "High Orthographic Complex - Low Orthographic Complex",
           "High Orthographic Simple - Low Orthographic Simple")

(emm2_contrasts_filtered <- subset(emm2_contrasts, contrast %in% keep2))
```

```
||  contrast                                              estimate    SE df t.ratio p.value
||  High Orthographic Simple - Low Orthographic Simple       0.628 0.500 58   1.256  0.2142
||  High Orthographic Complex - Low Orthographic Complex   -0.293 0.579 58  -0.506  0.6145
||
|| Results are averaged over the levels of: family_size
|| Degrees-of-freedom method: kenward-roger
```

```r
# Get Confidence Intervals
(emm2_contrasts_filtered_ci <- confint(emm2_contrasts_filtered))
```

```
||  contrast                                              estimate    SE df lower.CL upper.CL
||  High Orthographic Simple - Low Orthographic Simple       0.628 0.500 58   -0.373    1.629
||  High Orthographic Complex - Low Orthographic Complex   -0.293 0.579 58   -1.451    0.865
||
|| Results are averaged over the levels of: family_size
|| Degrees-of-freedom method: kenward-roger
|| Confidence level used: 0.95
```

```r
# Get effect sizes
# Get all pairwise effect sizes
effs2 <- eff_size(emm2, sigma = sigma(m2), edf = df.residual(m2))

# Remove the  redundant rows
(effs2_filtered <- subset(effs2, contrast %in% keep2))
```

```
||  contrast                                              effect.size    SE df lower.CL upper.CL
||  High Orthographic Simple - Low Orthographic Simple          0.445 0.354 58   -0.264    1.154
||  High Orthographic Complex - Low Orthographic Complex      -0.208 0.410 58   -1.028    0.613
||
|| Results are averaged over the levels of: family_size
|| sigma used for effect sizes: 1.412
|| Degrees-of-freedom method: inherited from kenward-roger when re-gridding
|| Confidence level used: 0.95
```

Only **low-orthographic participants** show a reliable complexity effect: N250 amplitudes are more negative for simple nonwords than for complex ones, particularly for large-family items ($d \approx 0.7$).

High-orthographic participants show no difference, indicating greater normalization or automatic segmentation.

```r
# Estimated marginal means for the Orthographic_Sensitivity * family_size * complexity interaction
(emm3 <- emmeans(anova_model_n250_nonwords, ~ Orthographic_Sensitivity * family_size * complexity))
```

```
||  Orthographic_Sensitivity family_size complexity emmean    SE   df lower.CL upper.CL
||  High Orthographic        Small       Simple     -0.633 0.346 59.6    -1.33   0.0594
||  Low Orthographic         Small       Simple     -1.236 0.396 59.6    -2.03  -0.4441
||  High Orthographic        Large       Simple     -0.478 0.372 59.4    -1.22   0.2655
||  Low Orthographic         Large       Simple     -1.131 0.425 59.4    -1.98  -0.2809
||  High Orthographic        Small       Complex    -0.596 0.396 59.2    -1.39   0.1963
||  Low Orthographic         Small       Complex    -0.500 0.453 59.2    -1.41   0.4065
||  High Orthographic        Large       Complex    -0.623 0.418 59.1    -1.46   0.2125
||  Low Orthographic         Large       Complex    -0.133 0.477 59.1    -1.09   0.8221
```

```
||
|| Degrees-of-freedom method: kenward-roger
|| Confidence level used: 0.95
```

```r
# Get all pairwise contrasts
emm3_contrasts <- contrast(emm3,  method = "pairwise", by = NULL, adjust = "none")
# emm3_contrasts

# Keep only the contrasts you want
# Simple effects of family_size at each level of complexity
# Simple effects of complexity at each level of family_size
keep3 <- c("High Orthographic Large Simple - High Orthographic Large Complex",
           "High Orthographic Small Simple - High Orthographic Small Complex",
           "Low Orthographic Large Simple - Low Orthographic Large Complex",
           "Low Orthographic Small Simple - Low Orthographic Small Complex",
           "High Orthographic Small Simple - High Orthographic Large Simple",
           "High Orthographic Small Complex - High Orthographic Large Complex",
           "Low Orthographic Small Simple - High Orthographic Large Simple",
           "Low Orthographic Small Complex - Low Orthographic Large Complex",
           "High Orthographic Large Simple - Low Orthographic Large Simple",
           "High Orthographic Large Complex - Low Orthographic Large Complex",
           "High Orthographic Small Simple - Low Orthographic Small Simple",
           "High Orthographic Small Complex - Low Orthographic Small Complex")

(emm3_contrasts_filtered <- subset(emm3_contrasts, contrast %in% keep3))
```

```
||  contrast                                                          estimate    SE   df t.ratio p.value
||  High Orthographic Small Simple - Low Orthographic Small Simple      0.6030 0.526 59.6   1.147  0.2561
||  High Orthographic Small Simple - High Orthographic Large Simple    -0.1551 0.287 68.4  -0.541  0.5903
||  High Orthographic Small Simple - High Orthographic Small Complex   -0.0366 0.352 64.6  -0.104  0.9176
||  Low Orthographic Small Simple - High Orthographic Large Simple     -0.7581 0.543 79.4  -1.396  0.1665
||  Low Orthographic Small Simple - Low Orthographic Small Complex     -0.7359 0.403 64.6  -1.827  0.0724
||  High Orthographic Large Simple - Low Orthographic Large Simple      0.6532 0.564 59.4   1.157  0.2519
||  High Orthographic Large Simple - High Orthographic Large Complex    0.1450 0.352 64.6   0.412  0.6819
||  Low Orthographic Large Simple - Low Orthographic Large Complex     -0.9978 0.403 64.6  -2.477  0.0159
||  High Orthographic Small Complex - Low Orthographic Small Complex   -0.0964 0.602 59.2  -0.160  0.8733
||  High Orthographic Small Complex - High Orthographic Large Complex   0.0266 0.287 68.4   0.093  0.9265
||  Low Orthographic Small Complex - Low Orthographic Large Complex    -0.3667 0.328 68.4  -1.119  0.2672
||  High Orthographic Large Complex - Low Orthographic Large Complex   -0.4897 0.634 59.1  -0.772  0.4432
||
|| Degrees-of-freedom method: kenward-roger
```

```r
# Get Confidence Intervals
(emm3_contrasts_filtered_ci <- confint(emm3_contrasts_filtered))
```

```
||  contrast                                                          estimate    SE   df lower.CL upper.CL
||  High Orthographic Small Simple - Low Orthographic Small Simple      0.6030 0.526 59.6   -0.449   1.6549
||  High Orthographic Small Simple - High Orthographic Large Simple    -0.1551 0.287 68.4   -0.727   0.4169
||  High Orthographic Small Simple - High Orthographic Small Complex   -0.0366 0.352 64.6   -0.740   0.6671
||  Low Orthographic Small Simple - High Orthographic Large Simple     -0.7581 0.543 79.4   -1.839   0.3225
||  Low Orthographic Small Simple - Low Orthographic Small Complex     -0.7359 0.403 64.6   -1.541   0.0687
||  High Orthographic Large Simple - Low Orthographic Large Simple      0.6532 0.564 59.4   -0.476   1.7826
||  High Orthographic Large Simple - High Orthographic Large Complex    0.1450 0.352 64.6   -0.559   0.8487
||  Low Orthographic Large Simple - Low Orthographic Large Complex     -0.9978 0.403 64.6   -1.802  -0.1931
||  High Orthographic Small Complex - Low Orthographic Small Complex   -0.0964 0.602 59.2   -1.301   1.1078
||  High Orthographic Small Complex - High Orthographic Large Complex   0.0266 0.287 68.4   -0.545   0.5986
||  Low Orthographic Small Complex - Low Orthographic Large Complex    -0.3667 0.328 68.4   -1.021   0.2874
||  High Orthographic Large Complex - Low Orthographic Large Complex   -0.4897 0.634 59.1   -1.759   0.7795
||
|| Degrees-of-freedom method: kenward-roger
|| Confidence level used: 0.95
```

```r
# Get effect sizes
# Get all pairwise effect sizes
effs3 <- eff_size(emm3, sigma = sigma(m2), edf = df.residual(m2))

# Remove the  redundant rows
(effs3_filtered <- subset(effs3, contrast %in% keep3))
```

```
||  contrast                                                          effect.size    SE   df lower.CL upper.CL
||  High Orthographic Small Simple - Low Orthographic Small Simple         0.4270 0.372 59.6   -0.318   1.1720
||  High Orthographic Small Simple - High Orthographic Large Simple       -0.1098 0.203 59.4   -0.516   0.2964
||  High Orthographic Small Simple - High Orthographic Small Complex      -0.0259 0.249 59.2   -0.525   0.4732
||  Low Orthographic Small Simple - High Orthographic Large Simple        -0.5368 0.385 59.4   -1.306   0.2326
||  Low Orthographic Small Simple - Low Orthographic Small Complex        -0.5212 0.285 59.2   -1.092   0.0499
||  High Orthographic Large Simple - Low Orthographic Large Simple         0.4625 0.400 59.4   -0.337   1.2624
||  High Orthographic Large Simple - High Orthographic Large Complex       0.1027 0.249 59.1   -0.396   0.6019
||  Low Orthographic Large Simple - Low Orthographic Large Complex        -0.7066 0.285 59.1   -1.278  -0.1353
||  High Orthographic Small Complex - Low Orthographic Small Complex      -0.0683 0.426 59.2   -0.921   0.7845
||  High Orthographic Small Complex - High Orthographic Large Complex      0.0188 0.203 59.1   -0.387   0.4250
||  Low Orthographic Small Complex - Low Orthographic Large Complex       -0.2597 0.232 59.1   -0.724   0.2049
||  High Orthographic Large Complex - Low Orthographic Large Complex      -0.3468 0.449 59.1   -1.246   0.5521
```

```
||
|| sigma used for effect sizes: 1.412
|| Degrees-of-freedom method: inherited from kenward-roger when re-gridding
|| Confidence level used: 0.95
```

- For low-orthographic participants, the N250 is more negative overall (especially for simple items).
- For high-orthographic participants, N250 amplitudes are relatively stable across *complexity* and *family size*.
- The trend-level `Orthographic_Sensitivity × Complexity` effect arises because low-sensitivity participants show a stronger complexity contrast (more negative for simple than complex), while high-sensitivity participants do not.

4.2.1 Interaction Contrasts

The interaction contrast tests whether the difference in the complexity effect for large vs small families differs across sensitivity?

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

```
#  Interaction contrasts (difference-of-differences)
#    Compare complexity effect in large vs small family)
contrast(emm3, interaction = "pairwise", by = NULL, adjust = "holm")
```

```
||  Orthographic_Sensitivity_pairwise    family_size_pairwise complexity_pairwise estimate    SE   df t.ratio p.value
||  High Orthographic - Low Orthographic Small - Large        Simple - Complex      -0.444 0.245 1498  -1.808  0.0708
||
|| Degrees-of-freedom method: kenward-roger
```

```
confint(contrast(emm3, interaction = c("pairwise", "pairwise")))
```

```
||  Orthographic_Sensitivity_pairwise    family_size_pairwise complexity_pairwise estimate    SE   df lower.CL upper.CL
||  High Orthographic - Low Orthographic Small - Large        Simple - Complex      -0.444 0.245 1498   -0.925   0.0376
||
|| Degrees-of-freedom method: kenward-roger
|| Confidence level used: 0.95
```

```
# Compute the A1 - A2 difference within each combination of B × C
(complexity_diff <- contrast(emm3, method = "revpairwise",
                            by = c("Orthographic_Sensitivity", "family_size"),
                            simple = "complexity"))
```

```
|| Orthographic_Sensitivity = High Orthographic, family_size = Small:
||  contrast         estimate    SE   df t.ratio p.value
||  Complex - Simple   0.0366 0.352 64.6   0.104  0.9176
||
|| Orthographic_Sensitivity = Low Orthographic, family_size = Small:
||  contrast         estimate    SE   df t.ratio p.value
||  Complex - Simple   0.7359 0.403 64.6   1.827  0.0724
||
|| Orthographic_Sensitivity = High Orthographic, family_size = Large:
||  contrast         estimate    SE   df t.ratio p.value
||  Complex - Simple  -0.1450 0.352 64.6  -0.412  0.6819
||
|| Orthographic_Sensitivity = Low Orthographic, family_size = Large:
||  contrast         estimate    SE   df t.ratio p.value
||  Complex - Simple   0.9978 0.403 64.6   2.477  0.0159
||
|| Degrees-of-freedom method: kenward-roger
```

```
# Compute how that A-effect changes across the levels of B, separately for each level of C
(family_size_complexity_int_within_sensitivity <- contrast(complexity_diff,
                                                           method = "revpairwise",
                                                           by = "Orthographic_Sensitivity", simple = "family_size"))
```

```
|| contrast = Complex - Simple, Orthographic_Sensitivity = High Orthographic:
||  contrast1     estimate    SE   df t.ratio p.value
||  Large - Small   -0.182 0.161 1498  -1.125  0.2607
||
|| contrast = Complex - Simple, Orthographic_Sensitivity = Low Orthographic:
||  contrast1     estimate    SE   df t.ratio p.value
||  Large - Small    0.262 0.185 1498   1.418  0.1563
||
|| Degrees-of-freedom method: kenward-roger
```

```
# Get confidence intervals
confint(family_size_complexity_int_within_sensitivity)
```

```
|| contrast = Complex - Simple, Orthographic_Sensitivity = High Orthographic:
||  contrast1     estimate    SE   df lower.CL upper.CL
||  Large - Small   -0.182 0.161 1498   -0.498    0.135
||
|| contrast = Complex - Simple, Orthographic_Sensitivity = Low Orthographic:
||  contrast1     estimate    SE   df lower.CL upper.CL
```

```
||  Large - Small    0.262 0.185 1498   -0.100    0.624
||
|| Degrees-of-freedom method: kenward-roger
|| Confidence level used: 0.95
```

```
1.  Within the **high-orthographic group**, N250 amplitudes are fairly stable. There are no consistent effects of complexity or family size. All a

2.  Within the **low-orthographic group**, there is a clear complexity effect.

- Large-family nonwords: Simple = -1.13 µV vs. Complex = -0.13 µV --> strong difference (~1 µV).

- Small-family nonwords: Simple = -1.24 µV vs. Complex = -0.50 µV → moderate difference (~0.7 µV).
```

The complexity effect (Simple < Complex) is present for both family sizes but is stronger for large-family items.

```
3.  The complexity effect depends on both family size and sensitivity: For high-orthographic participants there is essentially no complexity effec
```

That pattern—where the complexity effect appears only for low-orthographic participants and is amplified for large-family items—is what drives the marginal 3-way interaction.

N250 amplitude (µV, more negative = larger N250)

	Complex	Simple	Delta(Simple–Complex)
High-Ortho Large	-0.62	-0.48	+0.14 (≈ 0)
High-Ortho Small	-0.60	-0.63	-0.03 (≈ 0)
Low-Ortho Large	-0.13	-1.13	-1.00 (large)
Low-Ortho Small	-0.50	-1.24	-0.74 (moderate)

The marginal three-way interaction reflects that the complexity effect on the N250 (more negative for simple than complex nonwords) occurs only among participants low in orthographic sensitivity, and this effect is strongest when the nonwords are derived from large morphological families.

In contrast, high-orthographic participants show similar N250 amplitudes across all combinations of family size and complexity, indicating more uniform, automatized form processing.

Thus, the three-way pattern suggests that individuals with weaker orthographic representations rely more heavily on morphological cues: when these cues are abundant (large family, complex form), processing is easier (less negative N250), but when such cues are sparse (large family, simple form), processing is effortful (more negative N250).

4.3 Plots

```r
p3 <- emmip(anova_model_n250_nonwords, family_size  ~ complexity | Orthographic_Sensitivity) + my_style
p4 <- emmip(anova_model_n250_nonwords, complexity  ~ family_size | Orthographic_Sensitivity) + my_style

plot_grid(p3, p4, ncol = 2)
```