M21 LDT ERP HC SEMANTIC SENSITIVITY N250 Family Size

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1 Load data files

```r
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"))
erp_4A <- read_csv(file.path(dir_path, "fs_m21_ldt_mea_300500_050050_1_AB.csv"))
erp_4B <- read_csv(file.path(dir_path, "fs_m21_ldt_mea_300500_050050_1_BA.csv"))
dmg_lng_vsl <- read_csv(file.path(dir_path, "demo_lang_vsl_pca_hc.csv"))
```

```r
library(dplyr)

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

```r
  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

```r
#Fit ANOVA model
anova_model_n250_words_b <- mixed(
    value ~ Semantic_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 ~ Semantic_Sensitivity * family_size * base_freq + (1 +
|| Model:     family_size + base_freq | SubjID) + (1 | SubjID:chlabel)
|| Data: n250_words_b
||                                        Effect      df         F p.value
|| 1                        Semantic_Sensitivity   1, 58      0.77    .383
|| 2                                 family_size   1, 58      1.49    .228
|| 3                                   base_freq   1, 58      0.55    .459
|| 4            Semantic_Sensitivity:family_size   1, 58      0.32    .576
|| 5              Semantic_Sensitivity:base_freq   1, 58      0.01    .910
|| 6                       family_size:base_freq 1, 1498 32.72 ***   <.001
|| 7 Semantic_Sensitivity:family_size:base_freq 1, 1498 16.96 ***   <.001
|| ---
|| 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 ~ Semantic_Sensitivity + family_size + base_freq + (1 + family_size + base_freq | SubjID) + (1 | SubjID:chlabel) + Semantic_Sensitivity:f
||                                                        npar  logLik    AIC    LRT Df Pr(>Chisq)
|| <none>                                                   16 -4420.1 8872.2
|| family_size in (1 + family_size + base_freq | SubjID)   13 -4731.8 9489.6 623.40  3  < 2.2e-16 ***
|| base_freq in (1 + family_size + base_freq | SubjID)     13 -4639.5 9304.9 438.73  3  < 2.2e-16 ***
|| (1 | SubjID:chlabel)                                    15 -4617.1 9264.2 394.07  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
|| ---------------------------------------------------------------------------
|| Semantic_Sensitivity                       |           0.01 | [0.00, 1.00]
|| family_size                                |           0.02 | [0.00, 1.00]
|| base_freq                                  |       9.47e-03 | [0.00, 1.00]
|| Semantic_Sensitivity:family_size           |       5.43e-03 | [0.00, 1.00]
|| Semantic_Sensitivity:base_freq             |       2.22e-04 | [0.00, 1.00]
|| family_size:base_freq                      |           0.02 | [0.01, 1.00]
|| Semantic_Sensitivity:family_size:base_freq |           0.01 | [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: 0.790
||      Marginal R2: 0.015
```

3.2 Main Effects

No significant main effects

3.3 Interactions

Effect	df	F	p.value	
family__size:base__freq	1, 1498	32.72 ***	<.001	0.02
Semantic__Sensitivity:family__size:base__freq	1, 1498	16.96 ***	<.001	0.01

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      -0.851 0.280 59.4   -1.412   -0.290
||  Small       High      -0.823 0.357 58.8   -1.537   -0.110
||  Large       Low       -0.341 0.294 59.2   -0.929    0.247
||  Small       Low       -1.005 0.351 58.9   -1.706   -0.303
||
|| Results are averaged over the levels of: Semantic_Sensitivity
|| Degrees-of-freedom method: kenward-roger
|| Confidence level used: 0.95
```

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

# 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",
          "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  -0.0273 0.268 64.4  -0.102  0.9190
||  Large High - Large Low   -0.5095 0.229 67.0  -2.230  0.0291
||  Small High - Small Low    0.1812 0.229 67.0   0.793  0.4305
||  Large Low - Small Low     0.6634 0.268 64.4   2.478  0.0158
||
|| Results are averaged over the levels of: Semantic_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  -0.0273 0.268 64.4   -0.562   0.5074
||  Large High - Large Low   -0.5095 0.229 67.0   -0.966  -0.0534
||  Small High - Small Low    0.1812 0.229 67.0   -0.275   0.6373
||  Large Low - Small Low     0.6634 0.268 64.4    0.129   1.1981
||
|| Results are averaged over the levels of: Semantic_Sensitivity
```

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

```
# 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 High - Small Low",
                                                   "Small High - Large Low")))
```

```
||  contrast                effect.size    SE   df lower.CL upper.CL
||  Large High - Small High     -0.0195 0.191 58.8  -0.4015   0.3625
||  Large High - Large Low      -0.3633 0.163 59.2  -0.6895  -0.0371
||  Small High - Small Low       0.1293 0.163 58.8  -0.1969   0.4554
||  Large Low - Small Low        0.4731 0.191 58.9   0.0908   0.8554
||
|| Results are averaged over the levels of: Semantic_Sensitivity
|| sigma used for effect sizes: 1.402
|| 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 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 (-0.027, p = .92). Family size doesn't matter when base frequency is high.
- At **Low Base Frequency**: `Large` vs. `Small` family; significant difference (0.66, p = .016). When base frequency is low, small-family words yield more negative amplitudes than large-family words
- Within **Small Family**: `High` vs. `Low` base frequency; not significant (0.18, p = .43). Small-family words are unaffected by base frequency.
- Within **Large Family**: High vs. Low base frequency → significant (-0.51, p = .029). Large-family words show more negative amplitudes when their base frequency is high.

3.3.2 Interaction Contrasts

```
#  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           -0.691 0.121 1498  -5.720  <.0001
||
|| Results are averaged over the levels of: Semantic_Sensitivity
|| Degrees-of-freedom method: kenward-roger
```

```
# 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  -0.0273 0.268 64.4   -0.562    0.507
||
|| base_freq = Low:
||  contrast      estimate    SE   df lower.CL upper.CL
||  Large - Small   0.6634 0.268 64.4    0.129    1.198
||
|| Results are averaged over the levels of: Semantic_Sensitivity
|| Degrees-of-freedom method: kenward-roger
|| Confidence level used: 0.95
```

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

```
||  family_size_pairwise base_freq_pairwise estimate    SE   df lower.CL upper.CL
||  Large - Small        High - Low           -0.691 0.121 1498   -0.928   -0.454
||
|| Results are averaged over the levels of: Semantic_Sensitivity
|| Degrees-of-freedom method: kenward-roger
|| Confidence level used: 0.95
```

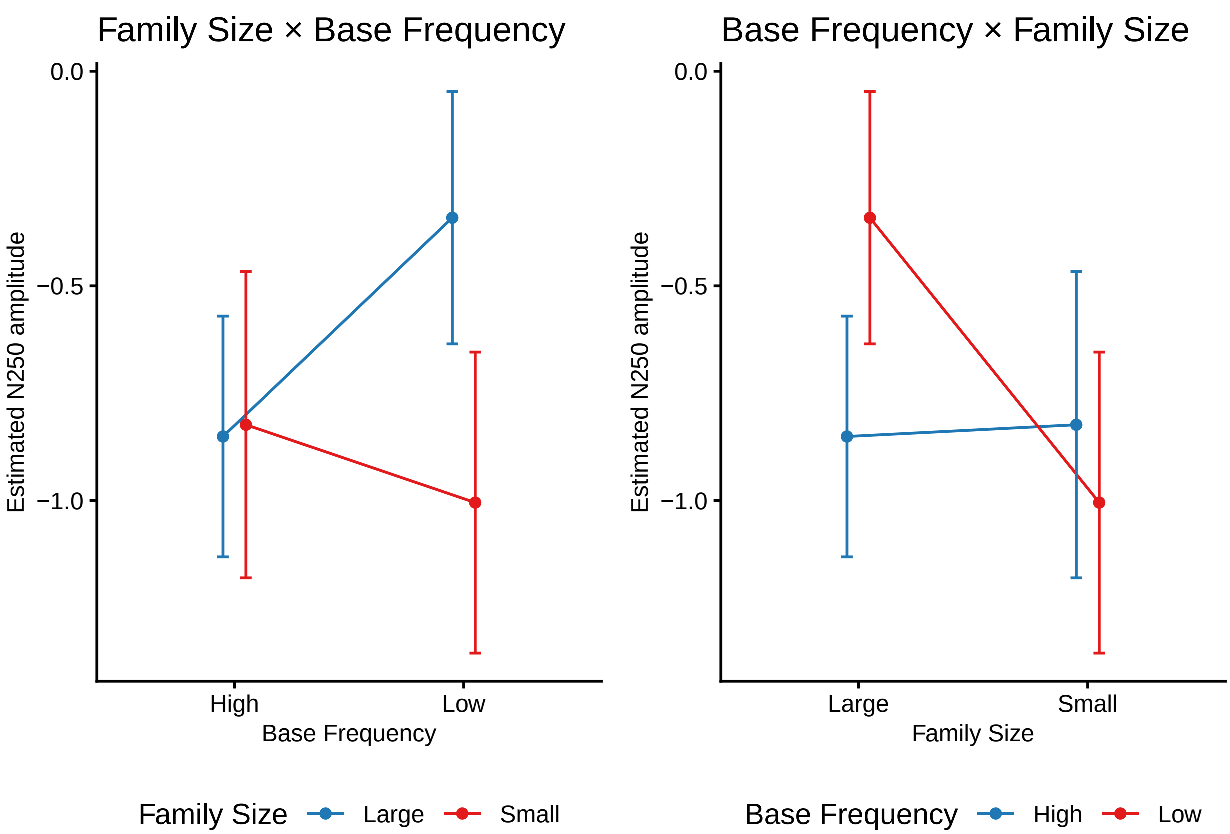
3.4 Plots

```
emm1_df <- as.data.frame(emm1)
p1<- ggplot(emm1_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)) +
```

```r
  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 = "Family Size × Base Frequency") +
  scale_color_custom() +
  scale_fill_custom()

p2 <- ggplot(emm1_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)
```



4 N250 Nonword Data

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

n250_nonwords |> filter(family_size == "complex")
```

4.1 Compute the ANOVA

```
anova_model_n250_nonwords <- mixed(
    value ~ Semantic_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 ~ Semantic_Sensitivity * family_size * complexity + (1 +
|| Model:     family_size + complexity | SubjID) + (1 | SubjID:chlabel)
|| Data: n250_nonwords
||                                          Effect      df      F p.value
|| 1                          Semantic_Sensitivity   1, 58   0.16    .687
|| 2                                   family_size   1, 58   0.42    .518
|| 3                                    complexity   1, 58   1.78    .187
|| 4             Semantic_Sensitivity:family_size   1, 58   0.31    .577
|| 5              Semantic_Sensitivity:complexity   1, 58   0.67    .416
|| 6                        family_size:complexity 1, 1498   0.03    .874
|| 7 Semantic_Sensitivity:family_size:complexity 1, 1498 4.71 *    .030
|| ---
|| 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 ~ Semantic_Sensitivity + family_size + complexity + (1 + family_size + complexity | SubjID) + (1 | SubjID:chlabel) + Semantic_Sensitivity
||                                                         npar  logLik    AIC    LRT Df Pr(>Chisq)
|| <none>                                                    16 -4428.3 8888.6
|| family_size in (1 + family_size + complexity | SubjID)   13 -4616.5 9259.0 376.42  3  < 2.2e-16 ***
|| complexity in (1 + family_size + complexity | SubjID)    13 -4740.1 9506.3 623.67  3  < 2.2e-16 ***
|| (1 | SubjID:chlabel)                                     15 -4631.2 9292.3 405.74  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
|| ---------------------------------------------------------------------------
|| Semantic_Sensitivity                        |       2.81e-03 | [0.00, 1.00]
|| family_size                                 |       7.26e-03 | [0.00, 1.00]
|| complexity                                  |           0.03 | [0.00, 1.00]
|| Semantic_Sensitivity:family_size            |       5.39e-03 | [0.00, 1.00]
|| Semantic_Sensitivity:complexity             |           0.01 | [0.00, 1.00]
|| family_size:complexity                      |       1.69e-05 | [0.00, 1.00]
|| Semantic_Sensitivity:family_size:complexity |       3.13e-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: 0.008
```

4.2 Main Effects

No main effects.

4.3 Interactions

A three way interaction between

- `Sensitivity × Family Size × Complexity`: significant (t = 4.71, p =.03).

4.3.1 Simple Contrasts

Compare High vs Low Semantic 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 Semantic 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?

```
# Estimated marginal means for the family_size × complexity interaction
(emm2 <- emmeans(anova_model_n250_nonwords, ~ Semantic_Sensitivity * family_size * complexity))
```

```
||  Semantic_Sensitivity family_size complexity emmean    SE   df lower.CL upper.CL
||  High Semantic        Small       Simple     -1.002 0.368 59.6    -1.74  -0.2651
||  Low Semantic         Small       Simple     -0.780 0.381 59.6    -1.54  -0.0182
||  High Semantic        Large       Simple     -0.629 0.392 59.4    -1.41   0.1557
||  Low Semantic         Large       Simple     -0.902 0.405 59.4    -1.71  -0.0915
||  High Semantic        Small       Complex    -0.743 0.413 59.2    -1.57   0.0823
||  Low Semantic         Small       Complex    -0.353 0.427 59.2    -1.21   0.5005
||  High Semantic        Large       Complex    -0.615 0.438 59.1    -1.49   0.2614
||  Low Semantic         Large       Complex    -0.193 0.453 59.1    -1.10   0.7130
||
|| Degrees-of-freedom method: kenward-roger
|| Confidence level used: 0.95
```

```
# Get all pairswise 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 Semantic Large Simple - High Semantic Large Complex",
           "High Semantic Small Simple - High Semantic Small Complex",
           "Low Semantic Large Simple - Low Semantic Large Complex",
           "Low Semantic Small Simple - Low Semantic Small Complex",
           "High Semantic Small Simple - High Semantic Large Simple",
           "High Semantic Small Complex - High Semantic Large Complex",
           "Low Semantic Small Simple - High Semantic Large Simple",
           "Low Semantic Small Complex - Low Semantic Large Complex",
           "High Semantic Large Simple - Low Semantic Large Simple",
           "High Semantic Large Complex - Low Semantic Large Complex",
           "High Semantic Small Simple - Low Semantic Small Simple",
           "High Semantic Small Complex - Low Semantic Small Complex")

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

```
||  contrast                                                  estimate    SE   df t.ratio p.value
||  High Semantic Small Simple - Low Semantic Small Simple      -0.222 0.529 59.6  -0.419  0.6766
||  High Semantic Small Simple - High Semantic Large Simple     -0.373 0.300 68.4  -1.244  0.2179
||  High Semantic Small Simple - High Semantic Small Complex    -0.258 0.376 64.3  -0.687  0.4947
||  Low Semantic Small Simple - High Semantic Large Simple      -0.151 0.546 78.9  -0.276  0.7830
||  Low Semantic Small Simple - Low Semantic Small Complex      -0.427 0.389 64.3  -1.097  0.2768
||  High Semantic Large Simple - Low Semantic Large Simple       0.274 0.564 59.4   0.486  0.6291
||  High Semantic Large Simple - High Semantic Large Complex    -0.014 0.376 64.3  -0.037  0.9705
||  Low Semantic Large Simple - Low Semantic Large Complex      -0.710 0.389 64.3  -1.824  0.0727
||  High Semantic Small Complex - Low Semantic Small Complex    -0.390 0.594 59.2  -0.657  0.5134
||  High Semantic Small Complex - High Semantic Large Complex   -0.129 0.300 68.4  -0.429  0.6694
||  Low Semantic Small Complex - Low Semantic Large Complex     -0.160 0.310 68.4  -0.517  0.6071
||  High Semantic Large Complex - Low Semantic Large Complex    -0.422 0.630 59.1  -0.670  0.5056
||
|| Degrees-of-freedom method: kenward-roger
```

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

```
||  contrast                                                  estimate    SE   df lower.CL upper.CL
||  High Semantic Small Simple - Low Semantic Small Simple      -0.222 0.529 59.6   -1.281   0.8374
||  High Semantic Small Simple - High Semantic Large Simple     -0.373 0.300 68.4   -0.971   0.2254
||  High Semantic Small Simple - High Semantic Small Complex    -0.258 0.376 64.3   -1.010   0.4931
||  Low Semantic Small Simple - High Semantic Large Simple      -0.151 0.546 78.9   -1.239   0.9366
||  Low Semantic Small Simple - Low Semantic Small Complex      -0.427 0.389 64.3   -1.204   0.3503
||  High Semantic Large Simple - Low Semantic Large Simple       0.274 0.564 59.4   -0.854   1.4020
||  High Semantic Large Simple - High Semantic Large Complex    -0.014 0.376 64.3   -0.765   0.7375
||  Low Semantic Large Simple - Low Semantic Large Complex      -0.710 0.389 64.3   -1.487   0.0673
||  High Semantic Small Complex - Low Semantic Small Complex    -0.390 0.594 59.2   -1.578   0.7973
```

```
||  High Semantic Small Complex - High Semantic Large Complex   -0.129 0.300 68.4   -0.727   0.4698
||  Low Semantic Small Complex - Low Semantic Large Complex     -0.160 0.310 68.4   -0.779   0.4585
||  High Semantic Large Complex - Low Semantic Large Complex    -0.422 0.630 59.1   -1.682   0.8384
||
|| 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 Semantic Small Simple - Low Semantic Small Simple       -0.15724 0.375 59.6   -0.908   0.5933
||  High Semantic Small Simple - High Semantic Large Simple      -0.26423 0.213 59.4   -0.689   0.1609
||  High Semantic Small Simple - High Semantic Small Complex     -0.18302 0.267 59.2   -0.716   0.3503
||  Low Semantic Small Simple - High Semantic Large Simple       -0.10699 0.387 59.4   -0.881   0.6675
||  Low Semantic Small Simple - Low Semantic Small Complex       -0.30224 0.276 59.2   -0.854   0.2492
||  High Semantic Large Simple - Low Semantic Large Simple        0.19399 0.400 59.4   -0.605   0.9933
||  High Semantic Large Simple - High Semantic Large Complex     -0.00991 0.267 59.1   -0.543   0.5234
||  Low Semantic Large Simple - Low Semantic Large Complex       -0.50274 0.276 59.1   -1.054   0.0489
||  High Semantic Small Complex - Low Semantic Small Complex     -0.27646 0.421 59.2   -1.118   0.5649
||  High Semantic Small Complex - High Semantic Large Complex    -0.09111 0.212 59.1   -0.516   0.3340
||  Low Semantic Small Complex - Low Semantic Large Complex      -0.11349 0.220 59.1   -0.553   0.3261
||  High Semantic Large Complex - Low Semantic Large Complex     -0.29884 0.446 59.1   -1.192   0.5940
||
|| sigma used for effect sizes: 1.411
|| Degrees-of-freedom method: inherited from kenward-roger when re-gridding
|| Confidence level used: 0.95
```

4.3.2 Interaction Contrasts

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

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

```r
#  Interaction contrasts (difference-of-differences)
#    Compare complexity effect in large vs small family)
contrast(emm2, interaction = "pairwise", by = NULL, adjust = "holm")
```

```
||  Semantic_Sensitivity_pairwise family_size_pairwise complexity_pairwise estimate    SE   df t.ratio p.value
||  High Semantic - Low Semantic  Small - Large        Simple - Complex      -0.527 0.243 1498  -2.169  0.0302
||
|| Degrees-of-freedom method: kenward-roger
```

```r
confint(contrast(emm2, interaction = c("pairwise", "pairwise")))
```

```
||  Semantic_Sensitivity_pairwise family_size_pairwise complexity_pairwise estimate    SE   df lower.CL upper.CL
||  High Semantic - Low Semantic  Small - Large        Simple - Complex      -0.527 0.243 1498       -1  -0.0505
||
|| Degrees-of-freedom method: kenward-roger
|| Confidence level used: 0.95
```

```r
# Compute the A1 - A2 difference within each combination of B × C
(complexity_diff <- contrast(emm2, method = "revpairwise",
                            by = c("Semantic_sensitivity", "family_size"),
                            simple = "complexity"))
```

```
|| Semantic_Sensitivity = High Semantic, family_size = Small:
||  contrast         estimate    SE   df t.ratio p.value
||  Complex - Simple    0.258 0.376 64.3   0.687  0.4947
||
|| Semantic_Sensitivity = Low Semantic, family_size = Small:
||  contrast         estimate    SE   df t.ratio p.value
||  Complex - Simple    0.427 0.389 64.3   1.097  0.2768
||
|| Semantic_Sensitivity = High Semantic, family_size = Large:
||  contrast         estimate    SE   df t.ratio p.value
||  Complex - Simple    0.014 0.376 64.3   0.037  0.9705
||
|| Semantic_Sensitivity = Low Semantic, family_size = Large:
||  contrast         estimate    SE   df t.ratio p.value
||  Complex - Simple    0.710 0.389 64.3   1.824  0.0727
||
|| Degrees-of-freedom method: kenward-roger
```

```r
# 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 = "Semantic_sensitivity", simple = "family_size"))
```

```
|| contrast = Complex - Simple, Semantic_Sensitivity = High Semantic:
||  contrast1     estimate    SE   df t.ratio p.value
||  Large - Small   -0.244 0.169 1498  -1.446  0.1484
||
|| contrast = Complex - Simple, Semantic_Sensitivity = Low Semantic:
||  contrast1     estimate    SE   df t.ratio p.value
||  Large - Small    0.283 0.175 1498   1.620  0.1055
||
|| Degrees-of-freedom method: kenward-roger
```

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

```
|| contrast = Complex - Simple, Semantic_Sensitivity = High Semantic:
||  contrast1     estimate    SE   df lower.CL upper.CL
||  Large - Small   -0.244 0.169 1498  -0.5758   0.0872
||
|| contrast = Complex - Simple, Semantic_Sensitivity = Low Semantic:
||  contrast1     estimate    SE   df lower.CL upper.CL
||  Large - Small    0.283 0.175 1498  -0.0598   0.6257
||
|| Degrees-of-freedom method: kenward-roger
|| Confidence level used: 0.95
```

Compute the effect of Complexity (Complex - Simple) within each Semantic Sensitivity × Family Size combination.

High Sensitivity- Small Family: `Complex - Simple = -0.743 - (-1.002) = +0.256`

High Sensitivity- Large Family: `Complex - Simple = -0.615 - (-0.629) = +0.014`

Low Sensitivity - Small Family: `Complex - Simple = -0.4267 - (-0.78) = +0.4277`

Low Sensitivity - Large Family: `Complex - Simple = -0.902 - (-0.902) = +0.709`

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`

```
-   $SE = 0.243$, $df = 1523$, $t = 2.140$ --> yields $p = 0.0325$, so it is statistically significant (given Bonferroni correction, etc.).
```

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.

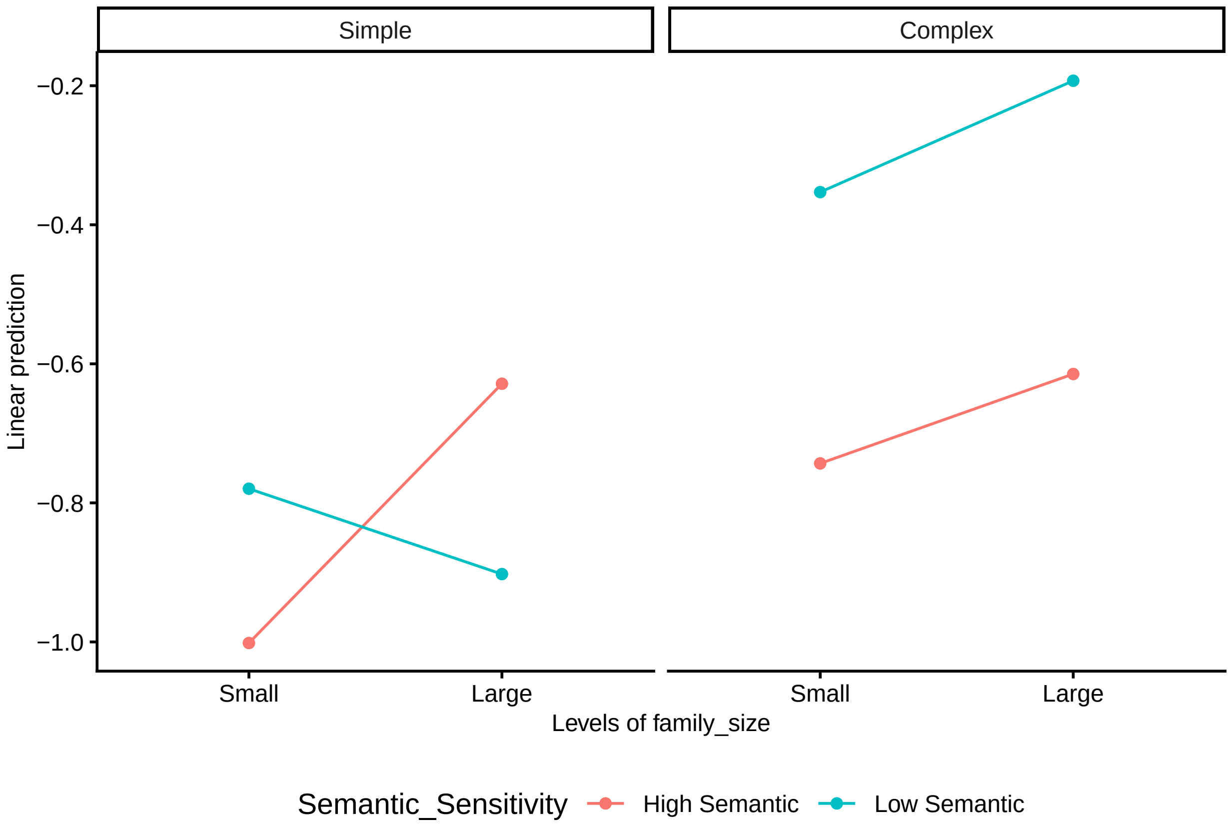
In `Small families`, `High sensitivity` participants respond more negatively to `complex items`, white `Low sensitivity` participants respond more negatively to `simple items`.

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

4.4 Plots

4.5 Plots

```r
emmip(anova_model_n250_nonwords, Semantic_Sensitivity ~ family_size  | complexity)
```



Interpretation - This is an interaction contrast (a "contrast of contrasts") across your three factors (Semantic 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 `Semantic Sensitivity`.

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

- The `estimate = 0.52` is the difference in differences (i.e. the slope difference) on your response metric (N250 amplitude).
- 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 Semantic readers show a different `complexity × family size` effect than Low Semantic 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 semantically 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. Semantic 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, semantic sensitivity may play a role in how multiple lexical factors are integrated during early morphological processing, though the effect is subtle.